Online Appendix

Predicting the Demand for Central Bank Digital Currency: A Structural Analysis with Survey Data

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November 9, 2022

A Asset Choices under Nested Logit Model

This section discusses the allocation of liquid assets among cash, deposits, and CBDC under a nested logit model, where CBDC can be a closer substitute for deposits in Section A.1 or for cash in Section A.2

A.1 CBDC and Deposits are Closer Substitutes

This section assumes CBDC and deposit are closer substitutes due to the correlated unobserved utilities. Section A.1.1 derives the deposit-to-cash ratio which implies the substitution pattern. Section A.1.1 shows how the deposit-to-cash ratio changes with the correlation coefficient. Section A.1.3 shows how the CBDC share changes with the correlation coefficient.

A.1.1 Substitution from Deposits and Cash into CBDC

Due to the correlated unobserved utilities within the nest, cash and deposits no longer substitute proportionally into CBDC. This section shows that when the correlation between the unobserved utilities of deposits and CBDC is positive, i.e., $\rho_{d\_cbdc} > 0$, the deposit-to-cash ratio becomes smaller than that before the CBDC issuance, which shows that the demand for CBDC draws more than proportionally from deposits.

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Suppose CBDC and deposits are in the same nest B_{d_cbdc}, then the deposit share is the conditional probability of choosing deposits from the nest B_{d_cbdc} multiplied by the probability of choosing the nest B_{d_cbdc}:

$$s'_{i,d,t} = \underbrace{\frac{\exp\left(\frac{V_{i,d,t}}{\tau_d}\right)}{\exp\left(\frac{V_{i,cbdc,t}}{\tau_d}\right) + \exp\left(\frac{V_{i,d,t}}{\tau_d}\right)}}_{\text{Prob}(j=d|j\in B_{d\_cbdc})} \underbrace{\frac{\left[\exp\left(\frac{V_{i,cbdc,t}}{\tau_d}\right) + \exp\left(\frac{V_{i,d,t}}{\tau_d}\right)\right]^{\tau_d}}{\left[\exp\left(\frac{V_{i,cbdc,t}}{\tau_d}\right) + \exp\left(\frac{V_{i,d,t}}{\tau_d}\right)\right]^{\tau_d} + \exp\left(V_{i,c,t}\right)}}_{\text{Prob}(j\in B_{d\_cbdc})} \tag{A1}$$

and the cash share is:

$$s'_{i,c,t} = \frac{\exp\left(V_{i,c,t}\right)}{\left[\exp\left(\frac{V_{i,cbdc,t}}{\tau_d}\right) + \exp\left(\frac{V_{i,d,t}}{\tau_d}\right)\right]^{\tau_d} + \exp\left(V_{i,c,t}\right)} \tag{A2}$$

where $\tau_d \equiv \sqrt{1-\rho_{d\_cbdc}} \in (0,1]$ is an inverse measure of the correlation $\rho_{d\_cbdc} \in [0,1)$ between the unobserved utilities for deposits and CBDC.

Divide the deposit share (A1) by the cash share (A2) to get the deposit-to-cash ratio after CBDC issuance:

$$\begin{aligned}
\frac{s'_{i,d,t}}{s'_{i,c,t}} &= \frac{\exp\left(\frac{V_{i,d,t}}{\tau_d}\right)\left[\exp\left(\frac{V_{i,d,t}}{\tau_d}\right) + \exp\left(\frac{V_{i,cbdc,t}}{\tau_d}\right)\right]^{\tau_d-1}}{\exp\left(V_{i,c,t}\right)} \\
&= \exp\left(V_{i,d,t} - V_{i,c,t}\right)\exp\left(\frac{V_{i,d,t}}{\tau_d} - V_{i,d,t}\right)\left[\exp\left(\frac{V_{i,d,t}}{\tau_d}\right) + \exp\left(\frac{V_{i,cbdc,t}}{\tau_d}\right)\right]^{\tau_d-1} \\
&= \left[1 + \exp\left(\frac{V_{i,cbdc,t} - V_{i,d,t}}{\tau_d}\right)\right]^{\tau_d-1} \exp\left(V_{i,d,t} - V_{i,c,t}\right)
\end{aligned} \tag{A3}$$

where $\exp\left(V_{i,d,t} - V_{i,c,t}\right) = \frac{s_{i,d,t}}{s_{i,c,t}}$ is the deposit-to-cash ratio before the CBDC issuance. When CBDC is a perfect substitute for deposits (i.e., $V_{i,cbdc,t} = V_{i,d,t}$ and τ_d approaches 0), the deposit-to-cash ratio after CBDC issuance is reduced by a half, since half of the deposits would be substituted into CBDC while cash is unaffected.

Since $\left[1 + \exp\left(\frac{V_{i,cbdc,t}-V_{i,d,t}}{\tau_d}\right)\right] > 1$ and $(\tau_d - 1) \leqslant 0$, it follows that the new deposit-to-cash ratio (A3) is a fraction $\theta_{i,t} \in (0,1]$ of the deposit-to-cash ratio before CBDC issuance.

$$\frac{s'_{i,d,t}}{s'_{i,c,t}} = \theta_{i,t}\frac{s_{i,d,t}}{s_{i,c,t}} \tag{A4}$$

Therefore, when $0 < \tau_d < 1$, the deposit-to-cash ratio $\frac{s'_{i,d,t}}{s'_{i,c,t}}$ becomes smaller than that before the CBDC issuance. This shows that the demand for CBDC draws more than proportionally from deposits.

A.1.2 The Impact of Correlation ρ_{d_cbdc} on Substitution Pattern

To see how the inverse correlation measure τ_d affects the deposit-to-cash ratio, differentiate (A3) with respect to τ_d to get:

$$\begin{aligned}
\frac{\partial \frac{s'_{i,d,t}}{s'_{i,c,t}}}{\partial \tau_d} &= \left[1+\exp\left(\frac{V_{i,cbdc,t}-V_{i,d,t}}{\tau_d}\right)\right]^{\tau_d-1} \ln\left(1+\exp\left(\frac{V_{i,cbdc,t}-V_{i,d,t}}{\tau_d}\right)\right)\frac{s_{i,d,t}}{s_{i,c,t}} \\
&\quad + (\tau_d-1)\left[1+\exp\left(\frac{V_{i,cbdc,t}-V_{i,d,t}}{\tau_d}\right)\right]^{\tau_d-2} \exp\left(\frac{V_{i,cbdc,t}-V_{i,d,t}}{\tau_d}\right)\left(-\frac{V_{i,cbdc,t}-V_{i,d,t}}{\tau_d^2}\right)\frac{s_{i,d,t}}{s_{i,c,t}} \\
&= \left(1+\frac{s_{i,cbdc,t}}{s'_{i,d,t}}\right)^{\tau_d-1}\frac{s_{i,d,t}}{s_{i,c,t}}\left[\ln\left(1+\frac{s_{i,cbdc,t}}{s'_{i,d,t}}\right)+(\tau_d-1)\frac{1}{1+\frac{s_{i,cbdc,t}}{s'_{i,d,t}}}\frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\partial \tau_d}\right] \\
&= \frac{s'_{i,d,t}}{s'_{i,c,t}}\left[\ln\left(1+\frac{s_{i,cbdc,t}}{s'_{i,d,t}}\right)+(\tau_d-1)\frac{1}{1+\frac{s_{i,cbdc,t}}{s'_{i,d,t}}}\frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\partial \tau_d}\right]
\end{aligned} \tag{A5}$$

As can be seen from (A5), how the deposit-to-cash ratio changes with τ_d depends on how the CBDC-to-deposit ratio $\frac{s_{i,cbdc,t}}{s'_{i,d,t}} = \exp\left(\frac{V_{i,cbdc,t}-V_{i,d,t}}{\tau_d}\right)$ changes with τ_d:

$$\frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\partial \tau_d} = \exp\left(\frac{V_{i,cbdc,t}-V_{i,d,t}}{\tau_d}\right)\left(-\frac{V_{i,cbdc,t}-V_{i,d,t}}{\tau_d^2}\right) \tag{A6}$$

which in turn depends on the sign of the observed utility difference $(V_{i,cbdc,t}-V_{i,d,t})$. When $V_{i,cbdc,t}-V_{i,d,t}>0$, the deposit-to-cash ratio increases in τ_d. This shows that the crowding-out effect on deposits is stronger if CBDC has a higher observed utility than deposits (i.e., $V_{i,cbdc,t}-V_{i,d,t}>0$). In contrast, when $V_{i,cbdc,t}-V_{i,d,t}\leqslant 0$, the deposit-to-cash ratio can decrease in τ_d.

A.1.3 The Impact of Correlation ρ_{d_cbdc} on CBDC share

Since the asset shares sum to one, i.e., $s'_{i,c,t}+s'_{i,d,t}+s_{i,cbdc,t}=1$, divide this identity by $s'_{i,d,t}$ and rearrange to write the CBDC share $s_{i,cbdc,t}$ in terms of the deposit-to-cash ratio:

$$s_{i,cbdc,t} = \frac{\frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{1+\frac{s'_{i,c,t}}{s'_{i,d,t}}+\frac{s_{i,cbdc,t}}{s'_{i,d,t}}} \tag{A7}$$

To see how $s_{i,cbdc,t}$ changes with τ_d, differentiate $s_{i,cbdc,t}$ (A7) with respect to τ_d:

$$\frac{\partial s_{i,cbdc,t}}{\partial \tau_d} = \frac{\frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\partial \tau_d}}{1+\frac{s'_{i,c,t}}{s'_{i,d,t}}+\frac{s_{i,cbdc,t}}{s'_{i,d,t}}} - \frac{\frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\left(1+\frac{s'_{i,c,t}}{s'_{i,d,t}}+\frac{s_{i,cbdc,t}}{s'_{i,d,t}}\right)^2}\left[-\left(\frac{s'_{i,d,t}}{s'_{i,c,t}}\right)^{-2}\frac{\partial \frac{s'_{i,d,t}}{s'_{i,c,t}}}{\partial \tau_d}+\frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\partial \tau_d}\right]$$
$$= \frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\partial \tau_d}\frac{1+\frac{s'_{i,c,t}}{s'_{i,d,t}}}{\left(1+\frac{s'_{i,c,t}}{s'_{i,d,t}}+\frac{s_{i,cbdc,t}}{s'_{i,d,t}}\right)^2} + \frac{\partial \frac{s'_{i,d,t}}{s'_{i,c,t}}}{\partial \tau_d}\frac{\frac{s_{i,cbdc,t}}{s'_{i,d,t}}\left(\frac{s'_{i,d,t}}{s'_{i,c,t}}\right)^{-2}}{\left(1+\frac{s'_{i,c,t}}{s'_{i,d,t}}+\frac{s_{i,cbdc,t}}{s'_{i,d,t}}\right)^2} \tag{A8}$$

Define $\Lambda \equiv \left(1+\frac{s'_{i,c,t}}{s'_{i,d,t}}+\frac{s_{i,cbdc,t}}{s'_{i,d,t}}\right)$ and substitute (A5) into (A8) to get:

$$\frac{\partial s_{i,cbdc,t}}{\partial \tau_d} = \frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\partial \tau_d}\frac{1+\frac{s'_{i,c,t}}{s'_{i,d,t}}}{\Lambda^2} + \frac{\frac{s_{i,cbdc,t}}{s'_{i,d,t}}\left(\frac{s'_{i,d,t}}{s'_{i,c,t}}\right)^{-2}}{\Lambda^2}\frac{s'_{i,d,t}}{s'_{i,c,t}}\left[\ln\left(1+\frac{s_{i,cbdc,t}}{s'_{i,d,t}}\right)+(\tau_d-1)\frac{1}{1+\frac{s_{i,cbdc,t}}{s'_{i,d,t}}}\frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\partial \tau_d}\right]$$
$$= \frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\partial \tau_d}\frac{1}{\Lambda^2}\left[1+\frac{s'_{i,c,t}}{s'_{i,d,t}}+\left(\frac{s'_{i,d,t}}{s'_{i,c,t}}\right)^{-1}\frac{(\tau_d-1)}{\frac{s'_{i,d,t}}{s_{i,cbdc,t}}+1}\right]+\frac{\frac{s_{i,cbdc,t}}{s'_{i,d,t}}\left(\frac{s'_{i,d,t}}{s'_{i,c,t}}\right)^{-1}}{\Lambda^2}\ln\left(1+\frac{s_{i,cbdc,t}}{s'_{i,d,t}}\right)$$
$$= \frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\partial \tau_d}\frac{1}{\Lambda^2}\left[1+\frac{s'_{i,c,t}}{s'_{i,d,t}}\left(1+\frac{(\tau_d-1)}{\frac{s'_{i,d,t}}{s_{i,cbdc,t}}+1}\right)\right]+\frac{\frac{s_{i,cbdc,t}}{s'_{i,d,t}}\frac{s'_{i,c,t}}{s'_{i,d,t}}}{\Lambda^2}\ln\left(1+\frac{s_{i,cbdc,t}}{s'_{i,d,t}}\right) \tag{A9}$$

Since $\tau_d \in (0,1]$ and $\frac{s'_{i,d,t}}{s_{i,cbdc,t}} > 0$, the term $\left(1+\frac{(\tau_d-1)}{\frac{s'_{i,d,t}}{s_{i,cbdc,t}}+1}\right)$ is positive. Hence, the sign of the derivative $\frac{\partial s_{i,cbdc,t}}{\partial \tau_d}$ depends on how the CBDC-to-deposit ratio $\frac{s_{i,cbdc,t}}{s'_{i,d,t}}$ changes with τ_d (A6), which in turn depends on the sign of the observed utility difference $(V_{i,cbdc,t} - V_{i,d,t})$.

Therefore, the impact of ρ_{d_cbdc} on the CBDC share depends on the difference in the observed utilities for CBDC and deposits, $(V_{i,cbdc,t} - V_{i,d,t})$. When $(V_{i,cbdc,t} - V_{i,d,t}) > 0$, it is ambiguous how the correlation affects the CBDC share. On the one hand, a higher ρ_{d_cbdc} makes CBDC and deposits more substitutable and thus leads to greater substitution from deposits to CBDC, which tends to raise the CBDC share. On the other hand, the higher correlation implies that the demand for CBDC would mainly draw from its closer substitute, deposits. As the cash demand is reduced by less, the share that can be allocated to deposits and CBDC is smaller, which tends to reduce the CBDC share. In contrast, when $(V_{i,cbdc,t} - V_{i,d,t}) \leqslant 0$, the former effect reinforces the latter and it is unambiguous that a higher correlation reduces the CBDC share.

A.2 CBDC and Cash are Closer Substitutes

Suppose CBDC and cash are closer substitutes along the unobserved dimensions and hence they are in the same nest. One example of the unobserved factor could be that people value the central-bank-issued money. Since CBDC and cash are both issued by the central bank and this feature cannot be identified empirically due to the lack of data, this can lead to a positive correlation ρ_{c_cbdc} between the unobserved utilities for CBDC and cash.

Section A.2.1 derives the new deposit-to-cash ratio as a factor of the old deposit-to-cash ratio before CBDC issuance, which implies the substitution pattern from deposits and cash into CBDC. Section A.2.1 shows how the deposit-to-cash ratio changes with the correlation coefficient. Section A.2.2 shows how the CBDC share changes with the correlation coefficient.

A.2.1 Substitution from Deposits and Cash into CBDC

If CBDC and cash are in the same nest, following similar steps in A.1.1, the deposit-to-cash ratio after CBDC issuance is:

$$\frac{s'_{i,d,t}}{s'_{i,c,t}} = \left[1 + \exp\left(\frac{V_{i,cbdc,t} - V_{i,c,t}}{\tau_c}\right)\right]^{1-\tau_c} \frac{s_{i,d,t}}{s_{i,c,t}} \tag{A10}$$

where $\tau_c \equiv \sqrt{1 - \rho_{c\_cbdc}} \in (0, 1]$ is an inverse measure of the correlation $\rho_{c\_cbdc} \in [0, 1)$ between the unobserved utilities for CBDC and cash, and $\frac{s_{i,d,t}}{s_{i,c,t}} = \exp\left(V_{i,d,t} - V_{i,c,t}\right)$ is the deposit-to-cash ratio before the CBDC issuance. Since $\left[1 + \exp\left(\frac{V_{i,cbdc,t} - V_{i,c,t}}{\tau_c}\right)\right] > 1$ and $(1 - \tau_c) \geqslant 0$, the factor $\left[1 + \exp\left(\frac{V_{i,cbdc,t} - V_{i,c,t}}{\tau_c}\right)\right]^{1-\tau_c} \geqslant 1$. As a consequence, $\frac{s'_{i,d,t}}{s'_{i,c,t}} \geqslant \frac{s_{i,d,t}}{s_{i,c,t}}$.

Therefore, when $\rho_{c\_cbdc} > 0$, the deposit-to-cash ratio is greater than that before CBDC issuance, which implies that the demand for CBDC draws more than proportionally from cash.

A.2.2 The Impact of Correlation ρ_{c_cbdc} on Substitution Pattern

To see how the inverse correlation measure τ_c affects the deposit-to-cash ratio, differentiate (A10) with respect to τ_c and simplify to get:

$$\frac{\partial \frac{s'_{i,d,t}}{s'_{i,c,t}}}{\partial \tau_c} = \frac{s'_{i,d,t}}{s'_{i,c,t}} \left[-\ln\left(1 + \frac{s_{i,cbdc,t}}{s'_{i,c,t}}\right) + (1 - \tau_c)\frac{1}{1 + \frac{s_{i,cbdc,t}}{s'_{i,c,t}}} \frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,c,t}}}{\partial \tau_c}\right] \tag{A11}$$

where $\frac{s_{i,cbdc,t}}{s'_{i,c,t}} = \exp\left(\frac{V_{i,cbdc,t}-V_{i,c,t}}{\tau_c}\right)$ and the derivative of $\frac{s_{i,cbdc,t}}{s'_{i,c,t}}$ with respect to τ_c is:

$$\frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,c,t}}}{\partial \tau_c} = \exp\left(\frac{V_{i,cbdc,t} - V_{i,c,t}}{\tau_c}\right)\left(-\frac{V_{i,cbdc,t} - V_{i,c,t}}{\tau_c^2}\right) \tag{A12}$$

As can be seen from (A11), how the deposit-to-cash ratio changes with τ_c depends on how the CBDC-to-cash ratio $\frac{s_{i,cbdc,t}}{s'_{i,c,t}}$ changes with τ_c (A12), which in turn depends on how the observed utility for CBDC compares with that for cash. When $V_{i,cbdc,t} - V_{i,c,t} \geqslant 0$, the deposit-to-cash ratio unambiguously decreases in τ_c. When $V_{i,cbdc,t} - V_{i,c,t} < 0$, the deposit-to-cash ratio can increase in τ_c.

A.2.3 The Impact of Correlation ρ_{c_cbdc} on CBDC Share

Divide the identity $s'_{i,c,t} + s'_{i,d,t} + s_{i,cbdc,t} = 1$ by $s'_{i,c,t}$ and rearrange to write the CBDC share $s_{i,cbdc,t}$ in terms of the deposit-to-cash ratio:

$$s_{i,cbdc,t} = \frac{\frac{s_{i,cbdc,t}}{s'_{i,c,t}}}{1 + \frac{s'_{i,d,t}}{s'_{i,c,t}} + \frac{s_{i,cbdc,t}}{s'_{i,c,t}}} \tag{A13}$$

To see how $s_{i,cbdc,t}$ changes with τ_c, differentiate $s_{i,cbdc,t}$ (A13) with respect to τ_c:

$$\begin{aligned} \frac{\partial s_{i,cbdc,t}}{\partial \tau_c} &= \frac{\frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,c,t}}}{\partial \tau_c}}{1 + \frac{s'_{i,d,t}}{s'_{i,c,t}} + \frac{s_{i,cbdc,t}}{s'_{i,c,t}}} - \frac{\frac{s_{i,cbdc,t}}{s'_{i,c,t}}}{\left(1 + \frac{s'_{i,d,t}}{s'_{i,c,t}} + \frac{s_{i,cbdc,t}}{s'_{i,c,t}}\right)^2}\left(\frac{\partial \frac{s'_{i,d,t}}{s'_{i,c,t}}}{\partial \tau_c} + \frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,c,t}}}{\partial \tau_c}\right) \\ &= \frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,c,t}}}{\partial \tau_c} \frac{1 + \frac{s'_{i,d,t}}{s'_{i,c,t}}}{\left(1 + \frac{s'_{i,d,t}}{s'_{i,c,t}} + \frac{s_{i,cbdc,t}}{s'_{i,c,t}}\right)^2} - \frac{\partial \frac{s'_{i,d,t}}{s'_{i,c,t}}}{\partial \tau_c} \frac{\frac{s_{i,cbdc,t}}{s'_{i,c,t}}}{\left(1 + \frac{s'_{i,d,t}}{s'_{i,c,t}} + \frac{s_{i,cbdc,t}}{s'_{i,c,t}}\right)^2} \end{aligned} \tag{A14}$$

Define $\Omega \equiv \left(1 + \frac{s'_{i,d,t}}{s'_{i,c,t}} + \frac{s_{i,cbdc,t}}{s'_{i,c,t}}\right)$. Substitute (A11) into (A14) and simplify to get:

$$\frac{\partial s_{i,cbdc,t}}{\partial \tau_c} = \frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,c,t}}}{\partial \tau_c} \frac{1}{\Omega^2}\left[1 + \frac{s'_{i,d,t}}{s'_{i,c,t}}\left(1 - \frac{(1-\tau_c)}{\frac{s'_{i,c,t}}{s_{i,cbdc,t}} + 1}\right)\right] + \frac{\frac{s_{i,cbdc,t}}{s'_{i,c,t}} \frac{s'_{i,d,t}}{s'_{i,c,t}}}{\Omega^2} \ln\left(1 + \frac{s_{i,cbdc,t}}{s'_{i,c,t}}\right) \tag{A15}$$

Since $\tau_c \in (0, 1]$ and $\frac{s'_{i,c,t}}{s_{i,cbdc,t}} > 0$, the term $\left(1 - \frac{(1-\tau_c)}{\frac{s'_{i,d,t}}{s_{i,cbdc,t}}+1}\right)$ is positive. Hence, how the CBDC share changes with τ_c depends on how the CBDC-to-deposit ratio $\frac{s_{i,cbdc,t}}{s'_{i,c,t}}$ changes with τ_c (A12), which in turn depends on the sign of the observed utility difference $(V_{i,cbdc,t} - V_{i,c,t})$.

Therefore, how the CBDC share changes with ρ_{c_cbdc} depends on the sign of the observed utility difference $(V_{i,cbdc,t} - V_{i,c,t})$. If $(V_{i,cbdc,t} - V_{i,c,t}) > 0$, it is ambiguous how the CBDC share is affected by the correlation. On the one hand, a higher ρ_{c_cbdc} tends to raise the CBDC share by making CBDC and cash more substitutable. On the other hand, as the demand for CBDC draws mainly from cash, deposits become less affected and thus the total share of CBDC and cash is lower, which tends to lower the CBDC share. In contrast, when $(V_{i,cbdc,t} - V_{i,c,t}) \leqslant 0$, the former effect is reversed and the CBDC share unambiguously decreases in ρ_{c_cbdc}.

B Asset Allocation Problem

Section B.1 shows that the log of deposit-to-cash ratio (3) derived from the logit model in the paper can also be derived from an asset allocation problem with money-in-the-utility assumptions and a constant-elasticity-of-substitution (CES) utility function. Section B.2 shows that the asset shares derived from the nested logit model in Section 2.2.2 can be equivalently obtained from an asset allocation problem with a nested CES utility function.

B.1 CES Utility

With the money-in-the-utility assumptions, households obtain the utility from holding cash c and deposits d since they can use the money holdings to facilitate transactions. Each household i maximizes the following CES utility function:[1]

$$u_{i,t}(q_{i,c,t}, q_{i,d,t}, \boldsymbol{x}_{i,c,t}, \boldsymbol{x}_{i,d,t}, \boldsymbol{z}_{i,t}) = \left[\nu_{i,c,t} q_{i,c,t}^{\theta} + \nu_{i,d,t} q_{i,d,t}^{\theta}\right]^{\frac{1}{\theta}} \tag{B16}$$

subject to a budget constraint:

$$q_{i,c,t} + q_{i,d,t} = w_{i,t} \tag{B17}$$

where $\theta \in (0, 1]$ is the substitution parameter and the estimate of the share parameter $\nu_{i,j,t}$ depends on the product attributes $\boldsymbol{x}_{i,j,t}$ and the household characteristics $\boldsymbol{z}_{i,t}$ for product $j \in \{c, d\}$. The interest on deposits or the opportunity cost of holding cash is included in the product attributes $\boldsymbol{x}_{i,j,t}$. The cash and deposit holdings are denoted by $q_{i,c,t}$ and $q_{i,d,t}$, respectively. This type of budget constraint, where wealth $w_{i,t}$ is allocated between different assets, follows Perraudin and Sørensen (2000). When θ approaches 0, the utility function becomes Cobb-Douglas. When θ is equal to one, the two assets are perfect substitutes, in

[1] See Kurlat (2019) and Drechsler, Savov and Schnabl (2017) for this type of asset allocation problem.

which case if $\nu_{i,j,t}$ from asset j is higher, then the entire wealth $w_{i,t}$ will be allocated to this asset.

Let λ denote the Lagrange multiplier associated with the budget constraint. Taking the first order conditions with respect to $q_{i,j,t}$ gives:

$$\frac{1}{\theta}\left[\nu_{i,c,t}q_{i,c,t}^{\theta}+\nu_{i,d,t}q_{i,d,t}^{\theta}\right]^{\frac{1}{\theta}-1}\nu_{i,j,t}\theta q_{i,j,t}^{\theta-1}=\lambda \quad \forall\ j\in\{c,d\} \tag{B18}$$

Divide the first order conditions with respect to $q_{i,d,t}$ and $q_{i,c,t}$ to get:

$$\frac{q_{i,d,t}}{q_{i,c,t}}=\left(\frac{\nu_{i,d,t}}{\nu_{i,c,t}}\right)^{\frac{1}{1-\theta}} \tag{B19}$$

Suppose $\nu_{i,j,t}$ can be represented by an exponential function of product attributes and household characteristics $\exp(V_{i,j,t}^{*})$, where $V_{i,j,t}^{*}=\boldsymbol{\alpha}^{*\prime}\boldsymbol{x}_{i,j,t}+\boldsymbol{\gamma}_j^{*\prime}\boldsymbol{z}_{i,t}+\eta_j^{*}$ is the observed part of the household's indirect utility (1) in the logit model before normalizing the scale of the utility.

Use $\nu_{i,j,t}=\exp(V_{i,j,t}^{*})$ and take logs of the deposit-to-cash ratio $\frac{q_{i,d,t}}{q_{i,c,t}}$ to get:

$$\ln\frac{q_{i,d,t}}{q_{i,c,t}}=\frac{1}{1-\theta}\left(V_{i,d,t}^{*}-V_{i,c,t}^{*}\right)=\frac{1}{1-\theta}\left[\boldsymbol{\alpha}^{*\prime}(\boldsymbol{x}_{i,d,t}-\boldsymbol{x}_{i,c,t})+\boldsymbol{\gamma}_d^{*\prime}\boldsymbol{z}_{i,t}+\eta_d^{*}\right] \tag{B20}$$

which is equivalent to the log of deposit-to-cash ratio (3) under the logit model except for the interpretation of the parameters. In this CES utility framework, the parameters (i.e., $\boldsymbol{\alpha}^{*}$, $\boldsymbol{\gamma}_d^{*}$, and η_d^{*}) are scaled by the degree of substitutability $(1-\theta)$ between deposits and cash. In contrast, under the logit model, these parameters are scaled by the standard deviation of the unobserved factors to normalize the scale of the utility. More specifically, the logit model implicitly scales the utilities for all products such that the variance of the unobserved factors is $\pi^2/6$. Let σ^{*} denote the original standard deviation of the unobserved factors in the logit model. The parameters $\boldsymbol{\alpha}^{*}$, $\boldsymbol{\gamma}_j^{*}$, and η_j^{*} are scaled by $\sqrt{\pi^2/6}/\sigma^{*}$.

B.2 Nested CES Utility

After introducing CBDC, suppose CBDC and deposits are closer substitutes and households hold them in bundles. The utility function has the following nested structure:

$$u_{i,t}(q_{i,c,t},q_{i,d,t},q_{i,cbdc,t},\boldsymbol{x}_{i,c,t},\boldsymbol{x}_{i,d,t},\boldsymbol{x}_{i,cbdc,t},\boldsymbol{z}_{i,t})=\left[\nu_{i,c,t}q_{i,c,t}^{\theta}+\nu_{i,d,t}\left[q_{i,d,t}^{\varphi}+\frac{\nu_{i,cbdc,t}}{\nu_{i,d,t}}q_{i,cbdc,t}^{\varphi}\right]^{\frac{\theta}{\varphi}}\right]^{\frac{1}{\theta}} \tag{B21}$$

and the budget constraint becomes:

$$q_{i,c,t} + q_{i,d,t} + q_{i,cbdc,t} = w_{i,t} \tag{B22}$$

where $\varphi \in (0,1]$ is the substitution parameter between CBDC and deposits, $\theta \in (0,1]$ is the substitution parameter between cash and the bundle, and $\nu_{i,j,t}$ is a share parameter for product $j \in \{c, d, cbdc\}$. When $\varphi = \theta$, the nest structure disappears. Here, the wealth $w_{i,t}$ is allocated into cash $q_{i,c,t}$, deposits $q_{i,d,t}$, and CBDC $q_{i,cbdc,t}$.

Let λ denote the Lagrange multiplier associated with the budget constraint. Take the first order conditions with respect to $q_{i,c,t}$, $q_{i,d,t}$, and $q_{i,cbdc,t}$ to get:

$$\frac{1}{\theta}\left[\nu_{i,c,t}q_{i,c,t}^{\theta} + \nu_{i,d,t}\left[q_{i,d,t}^{\varphi} + \frac{\nu_{i,cbdc,t}}{\nu_{i,d,t}}q_{i,cbdc,t}^{\varphi}\right]^{\frac{\theta}{\varphi}}\right]^{\frac{1}{\theta}-1} \nu_{i,c,t}\theta q_{i,c,t}^{\theta-1} = \lambda \tag{B23}$$

$$\frac{1}{\theta}\left[\nu_{i,c,t}q_{i,c,t}^{\theta} + \nu_{i,d,t}\left[q_{i,d,t}^{\varphi} + \frac{\nu_{i,cbdc,t}}{\nu_{i,d,t}}q_{i,cbdc,t}^{\varphi}\right]^{\frac{\theta}{\varphi}}\right]^{\frac{1}{\theta}-1} \nu_{i,d,t}\frac{\theta}{\varphi}\left[q_{i,d,t}^{\varphi} + \frac{\nu_{i,cbdc,t}}{\nu_{i,d,t}}q_{i,cbdc,t}^{\varphi}\right]^{\frac{\theta}{\varphi}-1} \varphi q_{i,d,t}^{\varphi-1} = \lambda \tag{B24}$$

$$\frac{1}{\theta}\left[\nu_{i,c,t}q_{i,c,t}^{\theta} + \nu_{i,d,t}\left[q_{i,d,t}^{\varphi} + \frac{\nu_{i,cbdc,t}}{\nu_{i,d,t}}q_{i,cbdc,t}^{\varphi}\right]^{\frac{\theta}{\varphi}}\right]^{\frac{1}{\theta}-1} \nu_{i,d,t}\frac{\theta}{\varphi}\left[q_{i,d,t}^{\varphi} + \frac{\nu_{i,cbdc,t}}{\nu_{i,d,t}}q_{i,cbdc,t}^{\varphi}\right]^{\frac{\theta}{\varphi}-1} \frac{\nu_{i,cbdc,t}}{\nu_{i,d,t}}\varphi q_{i,cbdc,t}^{\varphi-1} = \lambda \tag{B25}$$

Divide the first order conditions with respect to $q_{i,d,t}$ (B24) and $q_{i,cbdc,t}$ (B25) to get:

$$\frac{q_{i,d,t}}{q_{i,cbdc,t}} = \left(\frac{\nu_{i,d,t}}{\nu_{i,cbdc,t}}\right)^{\frac{1}{1-\varphi}} \tag{B26}$$

Divide the first order conditions with respect to $q_{i,d,t}$ (B24) and $q_{i,c,t}$ (B23) to get:

$$\frac{\nu_{i,d,t}\left[q_{i,d,t}^{\varphi} + \frac{\nu_{i,cbdc,t}}{\nu_{i,d,t}}q_{i,cbdc,t}^{\varphi}\right]^{\frac{\theta}{\varphi}-1} q_{i,d,t}^{\varphi-1}}{\nu_{i,c,t}q_{i,c,t}^{\theta-1}} = 1 \tag{B27}$$

which can be rearranged to:

$$\frac{\nu_{i,d,t}\left[1 + \frac{\nu_{i,cbdc,t}}{\nu_{i,d,t}}\frac{q_{i,cbdc,t}^{\varphi}}{q_{i,d,t}^{\varphi}}\right]^{\frac{\theta}{\varphi}-1} q_{i,d,t}^{\theta-1}}{\nu_{i,c,t}q_{i,c,t}^{\theta-1}} = 1 \tag{B28}$$

Using (B26) and (B28), the deposit-to-cash ratio after CBDC issuance can be written as:

$$\frac{q_{i,d,t}}{q_{i,c,t}} = \left(1 + \frac{q_{i,cbdc,t}}{q_{i,d,t}}\right)^{\frac{\varphi-\theta}{\varphi(\theta-1)}} \left(\frac{\nu_{i,d,t}}{\nu_{i,c,t}}\right)^{\frac{1}{1-\theta}} \tag{B29}$$

Note that when $\varphi = \theta$, this reduces to the CES utility case and the deposit-to-cash ratio is identical to (B19), which is independent from CBDC. This resembles the independence of irrelevant alternative property under the logit model.

Suppose $\nu_{i,j,t}$ is an exponential function of the product attributes and household characteristics, as in Appendix B.1. The deposit-to-cash ratio (B29) after CBDC issuance under the nested CES utility here is equivalent to that under the nested logit model (A3) when $\tau_d - 1 = \frac{\varphi-\theta}{\varphi(\theta-1)}$, where τ_d is the inverse measure of the correlation between the unobserved utilities for similar products under the nested logit.

It can be seen from Appendix B.1 that the deposit-to-cash ratio before the CBDC issuance is $\left(\frac{\nu_{i,d,t}}{\nu_{i,c,t}}\right)^{\frac{1}{1-\theta}}$. Hence, similar to the prediction from the nested logit model (A3), the deposit-to-cash ratio after the CBDC issuance is a fraction of that before the CBDC issuance, where the fraction depends on how CBDC is valued against deposits (indicated by $\frac{q_{i,cbdc,t}}{q_{i,d,t}}$) and the degree of substitutability between CBDC and deposits $\frac{\varphi-\theta}{\varphi(\theta-1)}$.

C Data

This section discusses the main data sources used in this paper. Section C.1 discusses the measures of cash holding, deposit holding, and the main financial institution, and shows the transaction frequency for different payment instruments using the CFM data. Section C.2 explains the construction of the online transaction frequency and the merchant acceptance rate using the 2013 MOP survey. Section C.3 discusses the demand deposit rates from CANNEX data. Section C.4 shows the construction of the sample weights in the merged sample of CFM and MOP survey data. Section C.5 shows the summary statistics.

C.1 Canadian Financial Monitor Survey

The CFM survey data are available from 1999, but the information on cash holding is only available from 2009. In addition, the CFM survey became an online survey after 2018, so the most recent data are less comparable with the offline surveys from previous years. This paper uses the sample period of 2010–2017 because the CFM survey questions on cash holdings are consistent across years during this period.

During 2010–2017, the question on cash in wallet is: “How much cash do you have in your purse or wallet right now?" and the question on precautionary cash holding is: "(On average), how much cash on hand does your household hold for emergencies, or other precautionary reasons?". Note that the phrase "on average" is included in the question for 2010–2012, while it is not included for 2013–2017. This difference is less of a concern after controlling for the year fixed effects. The results are robust to using the sample period of 2013–2017 only.

The survey questions on cash changed in 2009 and 2018. In 2009, the question on cash in wallet is, "On average, how much cash on hand was held for regular day-to-day use?". The question on precautionary cash holding also changed in 2018: "How much cash does your household hold outside your purse, wallet, or pockets right now?".

C.1.1 Cash Holding

In the baseline analysis, cash is measured by the sum of cash in wallet and precautionary cash holdings using the CFM data. There are two caveats: (1) cash in wallet is at an individual level while the precautionary cash holding is at a household level; (2) the answer for cash in wallet is in the nearest Canadian dollar, while that for the precautionary cash holding is in one of the following categories in Canadian dollars: none/zero, 1–49, 50–99, 100–249, 250–499, 500–999, 1000–2999, 3000 or more. I take the middle point of each category and if a household is in the top category (i.e., 3000 or more), I assume the precautionary cash holding for that household is 3000. Taking the upper bound at $3000 is similar to winsorizing the data at the 96th percentile, since around 4% of observations are in the top category during 2010–2017.

To address these two caveats, I check the results using the precautionary cash holding only, since the demand deposit balance is calculated at the household level and is also answered in one of the balance categories. The baseline results in the paper are robust using this alternative measure of cash. This is not surprising since the correlation between the total cash holding and the precautionary cash holding is around 0.98.

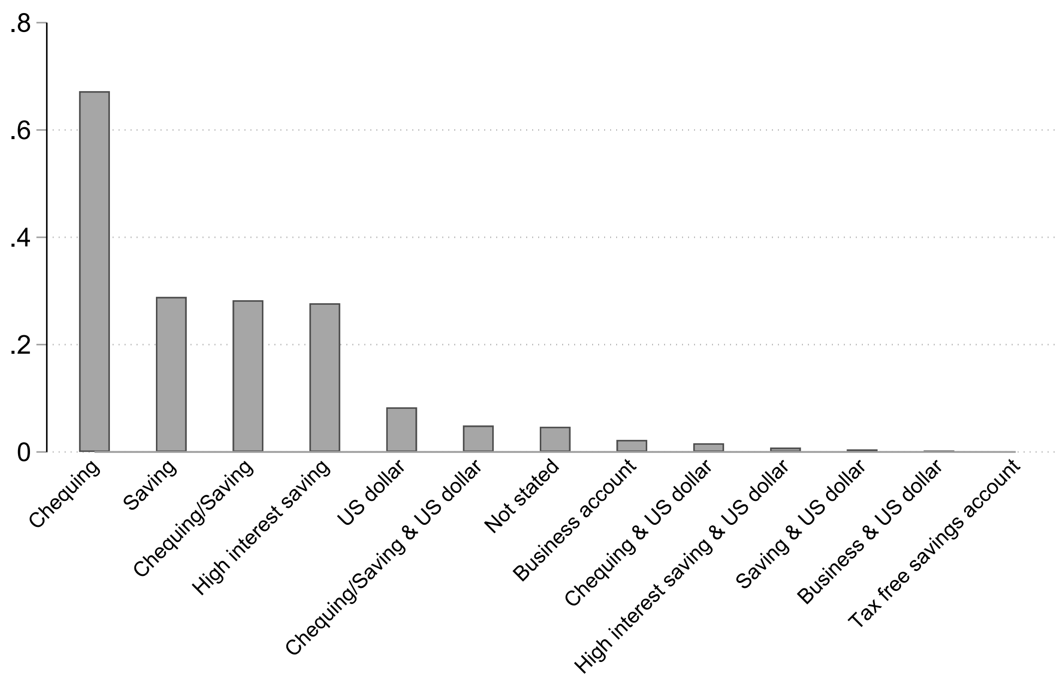
C.1.2 Deposit Holding

The CFM survey asks respondents to provide information on bank accounts (including the current balance, the type of account, associated financial institution, etc.) owned by each person in the household. The types of account include: chequing, saving, chequing/saving, high interest saving, chequing & US dollars, saving & US dollars, chequing/saving & US dollars, high interest saving & US dollars, etc.

The current balance in each bank account is answered in one of the following categories in Canadian dollars: non/zero, under 100, 100–499, 500–999, ..., 600,000–749,999, 750,000 or above. There are 38 categories between the smallest category (none/zero) and the highest category ($750K or over). I take the middle point of each category and if a household is in the top category (i.e., $750K or over), I assume the balance in the given bank account is $750K. In this paper, I focus on households' balances in demand deposit accounts (i.e., chequing, saving, chequing/saving accounts), where the maximum demand deposit balance across households is around $526K during 2010–2017.

Figure C1 shows the usage of all the bank account types that are classified in the CFM data. This paper focuses on the demand deposits measured by the sum of chequing, chequing/saving, and saving account balances, which can be readily used for transactions and thus are a close alternative to CBDC.

Figure C1: Fraction of Household-year Observations for Different Bank Accounts



Data source: CFM 2010–2017

Note: The bar chart shows the fraction of household-year observations that have a positive balance in a given type of bank account in the merged sample of CFM and MOP.

C.1.3 Main Financial Institution

There are two questions asking about the financial institutions (FIs) in the CFM survey. One question from section 1 of the survey is, "What is your main financial institution?".

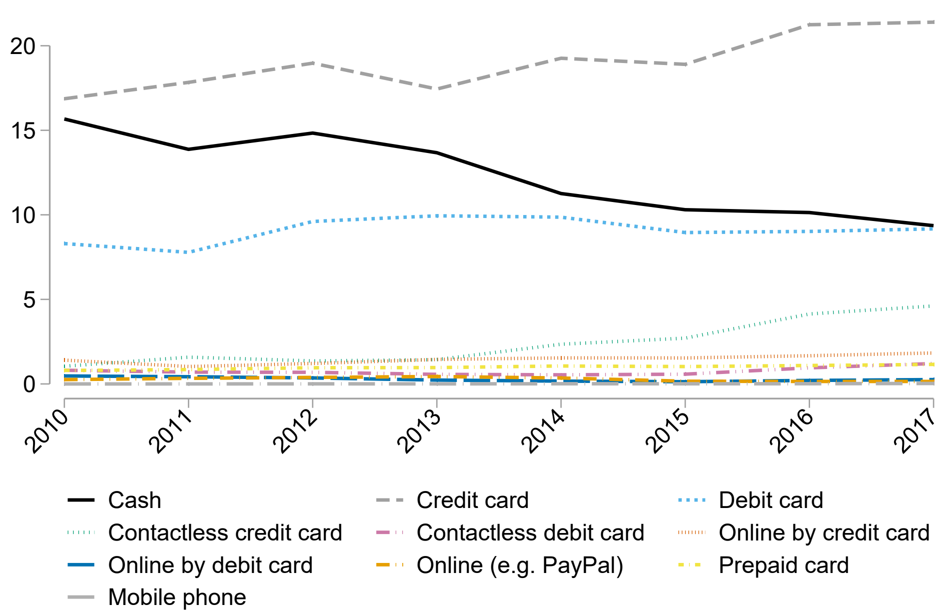
Each household can enter a maximum of three different main FIs, although around 67% of the household-year observations only enter one main FI. The other question on FIs is from the section on bank accounts in the survey, where the respondent needs to enter the FI associated with each bank account owned by each individual in the household.

Since this paper focuses on the demand deposits, I construct the main FI for each household using the information from the section on bank accounts. For each household, the FI that has the highest demand deposit balance is treated as the main FI. When different FIs have equal balances for a given household, the one that is treated as the main FI is the one that coincides with the main FI answered in section 1 of the survey.

C.1.4 Household Payment Patterns

Figure C2 shows the weighted mean number of transactions (in the past month) via each payment instrument across households in the merged sample. As can be seen, credit cards are used most frequently by Canadian households, followed by cash and debit cards.

Figure C2: Weighted Mean Number of Transactions (Past Month) across Households



Data source: CFM 2010–2017
Note: The graph plots the weighted mean number of transactions (in the past month) via each payment instrument across households in the merged sample of CFM 2010–2017 and MOP 2013, where the sample weights are applied. The survey question for each payment instrument usage (except for cash) is, "How many times has your household completed each of these transactions in the past month?". The survey question for cash usage is, "How many times did your household use cash to make purchases in the past week?". The answers for cash usage are multiplied by four to reflect the number of transactions in the past month.

C.2 Methods-of-Payment Survey 2013

This section explains how I measure the online payment capability feature and the merchant acceptance feature in more details.

C.2.1 Measuring Online Purchase Capability

From the MOP payment diary in 2013, each respondent records their transactions over a three-day period. A transaction is counted as online whenever the purchase is made online using a computer or a smartphone/tablet. Other choice categories for the location of purchase include at a store, over the phone, to another person, and by mail. For each respondent, the online transaction frequency is calculated as the number of online transactions over the total number of transactions recorded by this individual.

C.2.2 Measuring Merchant Acceptance

What matters for households' allocation between cash and deposits is not the aggregate-level merchant acceptance for cash or cards, but rather their own experience of the acceptance rate after optimizing which stores to visit. For example, if households prefer to visit the stores that do not accept cards after taking into account the factors such as the store location and the quality of the goods, they are likely to obtain more utility from holding cash and thus hold more cash relative to deposits.

Both the MOP survey questionnaire and the payment diary contain information on merchant acceptance. This section explains why I use the MOP payment diary to construct the merchant acceptance rate. There are two questions related to merchant acceptance from the MOP survey questionnaire. One question is to ask people whether they think acceptance is an important feature when considering how to pay. However, using these perceptions on the importance of acceptance feature could potentially lead to simultaneous causality. A person that prefers to use deposits to pay and hence holds more deposits may think acceptance is more important.

Another question from the survey questionnaire is to ask people whether they think a given payment instrument is widely accepted. The categories that people can choose from include: rarely accepted, occasionally accepted, often accepted, almost always accepted, and not sure. These perceptions tend to be less informative than the acceptance rate calculated using the payment diary because the perceptions of acceptance are not the only determinant for which stores people want to visit. They will also consider factors such as the location and the quality of the goods. For example, when some people perceive debit cards to be less widely accepted, this does not necessarily mean they would hold more cash and use cash to pay since they can avoid the cash-only stores or they may prefer to shop in the stores that accept cards anyway. In contrast, the card acceptance rates experienced by individuals through their own transactions tend to result from the individuals' optimal decisions in terms of which stores to visit, which are likely to matter more for their allocation between deposits and cash. Therefore, this paper uses the information from the MOP payment diary to construct the individual-level acceptance rate.

C.3 CANNEX Deposit Rates

CANNEX data are at a bank-product-week level. I average the weekly rates to get the annual rates. I use the deposit products from the high interest chequing category classified in CANNEX, because they are likely to be the most relevant for the demand deposit rates. Other categories of deposit products during the sample period include daily interest savings which are non-chequable and offer much higher deposit rates, daily interest chequing which tend to have rates close to zero throughout the sample period, daily interest investment for large balances, and senior and junior accounts that target particular groups of people. The high interest chequing accounts offer different tiers of interest rates, where the rate is higher for a larger balance. I take the average rate across different tiers to get the deposit rate of a given product. Each of the banks that I use has one product in this high interest chequing category except for CIBC which has two. To get the deposit rate at a bank-year level for CIBC, I average the deposit rates across the two products.

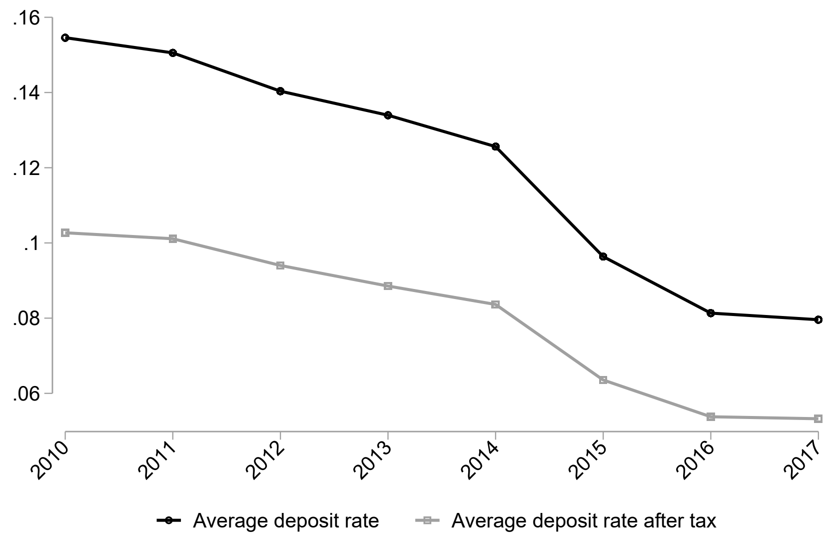
The deposit rates for the high interest chequing accounts are available for the big six, Laurentian Bank, Alterna Bank, Alterna Savings, and Manulife Bank over the sample period of 2010–2017. However, the latter three are not on the CFM choice list, so I use the deposit rates for the big six and Laurentian Bank which can be matched to the CFM data.

C.4 Sample Weights

To construct the sample weights for the merged sample of CFM 2010–2017 and MOP 2013, I use the population targets from National Household Survey 2011, Census 2011, and Census 2016 from StatCan. The sample weights are mainly used in calculating the descriptive statistics and estimating the weighted regression for robustness checks.

Table C1 in this section shows the population statistics in 2011 and 2016 only, due to the infrequency of the census data. The sample weights for the merged sample (covering the period of 2010–2017) of MOP and CFM are calibrated to target the statistics in year 2011 (2016) for the period of 2010–2013 (2014–2017). The population targets used in the weight calibration include household size, household income, household home ownership, and

Figure C3: Average Deposit Rates across Households over Time



Data sources: CANNEX 2010–2017, CFM 2010–2017, Government of Canada website
Note: The graph plots the average deposit rates before and after income taxes across households in the merged sample of CFM and MOP data. Households face different deposit rates (after taxes) as they save at different banks (and have different marginal income tax rates). The bank-level deposit rates are from CANNEX data and the federal and provincial income tax rates are from the Government of Canada website.

household head age, each nested within a given region (i.e., Atlantic and Prairies, Quebec, Ontario, British Columbia). As shown in Table C1, Atlantic region only accounts for 7% of the population, so it is combined with Prairies to ensure there are enough households in each stratum. The weighted sample data would match the population targets in Table C1. For example, the weighted fraction of households with a household size of one in Quebec would be 0.33.

I use the iterative proportional fitting to calibrate the weights in each year, which is commonly used in sample calibration as documented in Kolenikov (2014) and Vincent (2013). The first step is to specify the initial weights. I use the population totals over the number of households in the sample for each income-region category as initial weights. Using population totals over the number of households in the sample to generate the same initial weight for everyone does not affect the raking procedure and gives the same calibrated weights. The second step is to update the sample weights for each targeted demographic category in turn such that the weighted totals (of households) match the population counts in the given demographic category. The second step is repeated until the distances between the weighted totals and the population totals are minimized for all the targeted demographic categories.

Table C1: StatCan Targets for Private Households

(a) Population Statistics in 2016

	Atlantic	Quebec	Ontario	Prairies	BC	Canada
Region						
	0.07	0.25	0.37	0.17	0.13	1.00
Household Size						
1	0.28	0.33	0.26	0.25	0.29	0.28
2	0.40	0.35	0.33	0.34	0.35	0.34
3	0.16	0.14	0.16	0.15	0.15	0.15
4 or more	0.17	0.18	0.25	0.25	0.21	0.22
Household Income						
Less than 30K	0.21	0.21	0.17	0.14	0.19	0.18
30-60K	0.28	0.29	0.23	0.21	0.24	0.25
60-100K	0.25	0.25	0.25	0.24	0.25	0.25
More than 100K	0.26	0.24	0.35	0.41	0.32	0.32
Household Home Ownership						
Rent	0.27	0.39	0.30	0.27	0.32	0.32
Own	0.73	0.61	0.70	0.73	0.68	0.68
Household Head Age						
Under 34	0.15	0.17	0.16	0.21	0.17	0.17
35-44	0.15	0.17	0.17	0.19	0.16	0.17
45-54	0.20	0.19	0.22	0.20	0.20	0.20
55-64	0.21	0.21	0.20	0.19	0.21	0.20
65 or older	0.28	0.25	0.25	0.21	0.26	0.25

(b) Population Statistics in 2011

	Atlantic	Quebec	Ontario	Prairies	BC	Canada
Region						
	0.07	0.26	0.37	0.17	0.13	1.00
Household Size						
1	0.26	0.32	0.25	0.26	0.28	0.28
2	0.39	0.35	0.32	0.34	0.35	0.34
3	0.17	0.15	0.16	0.15	0.15	0.16
4 or more	0.19	0.18	0.26	0.24	0.22	0.23
Household Income						
Less than 30K	0.26	0.27	0.20	0.19	0.23	0.22
30-60K	0.29	0.30	0.26	0.24	0.26	0.27
60-100K	0.25	0.24	0.25	0.25	0.25	0.25
More than 100K	0.20	0.19	0.29	0.32	0.25	0.26
Household Home Ownership						
Rent	0.26	0.39	0.28	0.26	0.30	0.31
Own	0.74	0.61	0.72	0.74	0.70	0.69
Household Head Age						
Under 34	0.16	0.19	0.16	0.22	0.17	0.18
35-44	0.17	0.17	0.19	0.19	0.18	0.18
45-54	0.22	0.22	0.24	0.22	0.22	0.23
55-64	0.21	0.20	0.19	0.18	0.20	0.19
65 or older	0.25	0.23	0.23	0.19	0.23	0.22

Data sources: StatCan (Census 2016, Census 2011, National Household Survey 2011)
Note: Each cell represents the fraction of households under the given category.

C.5 Summary Statistics

This section shows the summary statistics for the key variables of interest.

Table C2: Ratings for Payment-specific Features

Ratings	1	2	3	4	5
Cost of use	Very low cost				Very high cost
Cash	0.74	0.14	0.10	0.02	0.00
Debit card	0.27	0.37	0.20	0.12	0.02
Credit card	0.17	0.22	0.17	0.29	0.14
Mobile payment app	0.05	0.10	0.71	0.10	0.02
Prepaid card	0.12	0.17	0.49	0.15	0.05
Ease/Convenience	Very hard to use				Very easy to use
Cash	0.00	0.01	0.04	0.17	0.76
Debit card	0.00	0.01	0.10	0.29	0.59
Credit card	0.01	0.01	0.07	0.31	0.60
Mobile payment app	0.04	0.13	0.63	0.13	0.04
Prepaid card	0.02	0.06	0.45	0.28	0.18
Security/Risk	Very risky				Very secure
Cash	0.01	0.07	0.11	0.26	0.54
Debit card	0.01	0.11	0.16	0.53	0.18
Credit card	0.02	0.13	0.16	0.53	0.15
Mobile payment app	0.09	0.22	0.54	0.11	0.02
Prepaid card	0.02	0.09	0.41	0.32	0.15

Data source: MOP 2013

Note: The table summarizes the weighted fraction of households choosing each rating (from a scale of one to five) for each feature of a given payment instrument, where the sample weights are applied to the merged sample of CFM 2013 and MOP 2013. For the cost, ease of use, and security features, the ratings of 1 to 5 represent very low- to very high-cost, very hard to very easy to use, and very risky to very secure, respectively.

Table C3: Summary Statistics

Variable	Obs	Mean	sd	Min	p25	p50	p75	Max
Dependent variable								
ln(deposit/cash)	5025	3.05	1.96	-4.20	1.84	3.10	4.31	10.13
Product Attributes								
Deposit rate (after tax)	5756	0.08	0.04	0.00	0.04	0.09	0.11	0.34
Attitudes towards bundling of service	6235	1.45	1.76	0.00	0.00	1.00	3.00	5.00
Difference in ratings for cost of use	6251	0.12	0.15	-0.50	0.00	0.13	0.20	0.57
Difference in ratings for ease of use	6243	-0.02	0.07	-0.50	-0.07	0.00	0.00	0.36
Difference in ratings for security	6264	-0.05	0.12	-0.57	-0.08	-0.07	0.00	0.57
Ratings for anonymity	6296	4.10	1.72	0.00	3.00	4.00	6.00	6.00
Ratings for budgeting usefulness	6279	3.70	1.82	0.00	3.00	4.00	5.00	6.00
Fraction of online transactions	5910	0.03	0.09	0.00	0.00	0.00	0.00	1.00
Fraction of transactions cards unaccepted	5910	0.06	0.14	0.00	0.00	0.00	0.00	1.00
Household Characteristics								
Household head age	6332	52.28	14.58	18.00	41.00	53.00	63.00	95.00
Household income	6208	7.55	3.36	1.00	5.00	8.00	10.00	12.00
Household size	6332	2.14	1.19	1.00	1.00	2.00	3.00	8.00
Household head education	6310	3.82	1.39	1.00	2.00	4.00	5.00	6.00
Dislike investing in stock market	6261	6.11	2.93	1.00	4.00	6.00	9.00	10.00
Have difficulty in paying off debt	6248	3.33	2.82	1.00	1.00	2.00	5.00	10.00
Behind debt obligations in the past year	6202	0.04	0.20	.	.	.	.	.
Rent a home	6200	0.27	0.44	.	.	.	.	.
Household has a female head	6332	0.77	0.42	.	.	.	.	.
Internet access at work/school/elsewhere	6332	0.40	0.49	.	.	.	.	.
Live in rural area	6332	0.16	0.37	.	.	.	.	.
Main financial institution (FI) is TD	5864	0.18	0.38	.	.	.	.	.
Main FI is RBC	5864	0.16	0.36	.	.	.	.	.
Main FI is Laurentian Bank	5864	0.01	0.09	.	.	.	.	.
Main FI is non-big six or Laurentian Bank	5864	0.33	0.47	.	.	.	.	.

Data sources: MOP 2013, CANNEX 2010–2017, CFM 2010–2017

Note: The table summarizes the number of observations, mean, standard deviation, minimum value, 25th percentile, median, 75th percentile, and maximum value for each given variable in the merged sample of CFM 2010–2017 and MOP 2013. The original scales for attitudes towards bundling of services and the ratings for anonymity and budgeting usefulness are changed, as discussed in Section 3. Difference in ratings refers to the difference in the standardized ratings between debit card and cash for a given feature. Household income and household head education are categorical variables. General attitudes towards stock market investment and debt obligations are on a scale of 1 (strongly disagree) to 10 (strongly agree), measuring the extent to which the respondent agrees with the corresponding statement. The last nine household characteristics are indicator variables that take a value of zero or one.

D Estimation Results

Section D.1 shows the baseline estimation results. Section D.2 discusses the robustness checks. Section D.3 checks the out-of-sample model fit.

D.1 Baseline Estimation Results

The estimated demand parameters (i.e., $\widehat{\boldsymbol{\alpha}}$, $\widehat{\boldsymbol{\gamma}}^d$, $\widehat{\eta}^d$) are separately saved in Table D4 and Table D5. While the preference parameters $\widehat{\boldsymbol{\alpha}}$ and the deposit-specific constant $\widehat{\eta}^d$ (i.e., constant in the regression) are saved in Table D4, the effects $\widehat{\boldsymbol{\gamma}}^d$ of household characteristics (including bank, region, and year fixed effects) are reported in Table D5.

Note that Table D4 contains more estimation specifications by adding one product attribute each time. Column (9) in the table is treated as the baseline results that are shown in the paper. Table D5 reports the other parameters estimated using specification (9) of Table D4.

Figure D4 shows the relative importance of different product features in explaining the deposit-to-cash ratio. For a given feature, its importance is measured by its contribution to the utility difference between deposits and cash, which in turn affects the deposit-to-cash ratio (3). Hence, each bar is computed using the attribute difference between deposits and cash multiplied by the corresponding preference parameter $\widehat{\alpha}(x_{i,d,t} - x_{i,c,t})$, which is then averaged across households and years. As can be seen, the most important attributes that affect the deposit-to-cash ratio are budgeting usefulness, anonymity, rate of return, and bundling of bank services. Ease of use and security features do not contribute a lot to the utility difference between deposits and cash because debit cards and cash are perceived to be relatively similar in terms of these attributes.

D.2 Robustness Checks

Table D6 in Appendix D.2 compares the baseline OLS regression with the weighted least squares (WLS) estimation by applying the sample weights. Detailed information on the sample weights for the matched sample of MOP and CFM can be found in Appendix C.4. The estimated preference parameters are similar, although the standard errors are higher under the WLS. I find that there is no significant difference between WLS and OLS, following the method in Deaton (2019, p. 72). This indicates that the sampling is independent of the dependent variable conditional on the explanatory variables, in which case weighting is unnecessary and harmful for precision (Solon, Haider and Wooldridge, 2013).

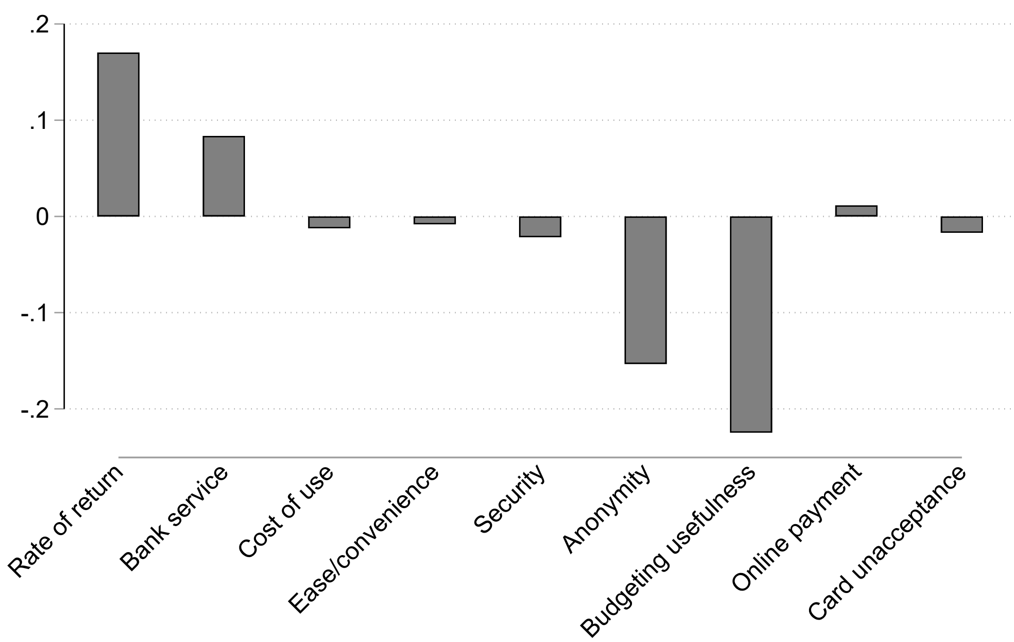
I also check whether the baseline results are robust to excluding various fixed effects. The

Table D4: Households' Preferences for Product Attributes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Deposit rate	2.114**	2.175**	2.208**	2.176**	2.167**	2.098**	2.263**	2.297**	2.191**
	(1.035)	(1.033)	(1.035)	(1.035)	(1.036)	(1.034)	(1.033)	(1.034)	(1.036)
Bank service		0.052***	0.051***	0.050***	0.050***	0.054***	0.060***	0.060***	0.059***
		(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Cost of use			-0.204	-0.150	-0.080	-0.087	-0.087	-0.102	-0.101
			(0.189)	(0.195)	(0.201)	(0.201)	(0.201)	(0.202)	(0.202)
Ease/Convenience				0.490	0.371	0.402	0.437	0.423	0.374
				(0.460)	(0.466)	(0.466)	(0.465)	(0.465)	(0.466)
Security					0.402	0.366	0.453*	0.444*	0.457*
					(0.256)	(0.256)	(0.256)	(0.256)	(0.256)
Anonymity						-0.058***	-0.039**	-0.038**	-0.038**
						(0.018)	(0.018)	(0.018)	(0.018)
Budgeting							-0.063***	-0.063***	-0.062***
							(0.018)	(0.017)	(0.017)
Online payment								0.425	0.439
								(0.312)	(0.314)
Card unacceptance									-0.282
									(0.181)
Constant	1.372***	1.318***	1.348***	1.391***	1.385***	1.594***	1.690***	1.672***	1.695***
	(0.381)	(0.380)	(0.382)	(0.384)	(0.384)	(0.389)	(0.387)	(0.388)	(0.388)
Observations	4,352	4,352	4,352	4,352	4,352	4,352	4,352	4,352	4,352
Adjusted R^2	0.062	0.064	0.064	0.064	0.064	0.067	0.069	0.069	0.070

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Data sources: CFM 2010–2017, MOP 2013, CANNEX 2010–2017, Government of Canada website
Note: The table shows the estimated preference parameters for the product attributes and the constant term from regressing the log of deposit-to-cash ratio on different product attributes and household characteristics (i.e., household income, household head age, female head indicator, household head education, home ownership, household size, rural area indicator, internet access at work, attitudes towards stock market investment, feeling difficulty in paying off debt, the indicator of being behind debt obligations in the past year, as well as the bank, region, and year fixed effects). The estimated parameters for household characteristics using specification (9) are shown in Table D5 of Appendix D.1.

Figure D4: Relative Importance of Different Product Attributes



Data sources: CFM 2010–2017, MOP 2013, CANNEX 2010–2017, Government of Canada website
Note: In this graph, the importance of a given product attribute is measured by its contribution to the utility difference between deposits and cash, which in turn affects the allocation of liquid assets between deposits and cash. For each attribute x, the bar is computed as the attribute difference between deposits and cash multiplied by the corresponding preference parameter $\widehat{\alpha}(x_{i,d,t} - x_{i,c,t})$ that is averaged across households and years. The y-axis is in utils.

Table D5: Estimated Parameters for Household Characteristics

	$\widehat{\gamma}_d$	se
Household head age 35–44	-0.277***	(0.106)
Household head age 45–54	-0.289***	(0.099)
Household head age 55–64	-0.223**	(0.105)
Household head age $\geqslant$ 65	-0.170	(0.122)
Household income \$15,000 - \$19,999	0.432**	(0.178)
Household income \$20,000 - \$24,999	0.476**	(0.187)
Household income \$25,000 - \$29,999	0.201	(0.185)
Household income \$30,000 - \$34,999	0.695***	(0.170)
Household income \$35,000 - \$44,999	0.648***	(0.155)
Household income \$45,000 - \$54,999	0.424***	(0.152)
Household income \$55,000 - \$59,999	0.713***	(0.184)
Household income \$60,000 - \$69,999	0.632***	(0.164)
Household income \$70,000 - \$99,999	0.768***	(0.148)
Household income \$100,000 - \$149,999	0.860***	(0.157)
Household income $\geqslant$ \$15,000	0.684***	(0.178)
Household size = 2	-0.239***	(0.084)
Household size = 3	-0.077	(0.106)
Household size $\geqslant$ 4	-0.421***	(0.108)
Grade 9-13	0.644**	(0.277)
Community College	0.664**	(0.283)
Diploma	0.759***	(0.279)
Undergraduate	0.767***	(0.280)
Post-graduate	0.918***	(0.286)
Rent a home	-0.261***	(0.078)
Household has a female head	0.283***	(0.086)
Have internet access at work/school/elsewhere	0.136*	(0.070)
Live in rural area	0.175**	(0.082)
Dislike investing in stock market	0.029**	(0.011)
Have difficulty in paying off debt	-0.075***	(0.012)
Behind debt obligations in the past year	-0.326*	(0.168)
Main financial institution (FI) is TD	0.152*	(0.091)
Main FI is RBC	-0.016	(0.106)
Main FI is Laurentian Bank	-0.852**	(0.397)
Main FI is not big six or Laurentian Bank	0.022	(0.092)
Year 2011	-0.042	(0.140)
Year 2012	-0.148	(0.133)
Year 2013	0.004	(0.124)
Year 2014	0.073	(0.129)
Year 2015	0.003	(0.134)
Year 2016	0.111	(0.139)
Year 2017	-0.023	(0.144)
Quebec	0.308**	(0.133)
Ontario	0.418***	(0.126)
Prairies	0.508***	(0.137)
British Columbia	0.560***	(0.140)
Observations	4,352	
Adjusted R^2	0.070	

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Data sources: CFM 2010–2017, MOP 2013, CANNEX 2010–2017, Government of Canada website
Note: The table shows the estimated parameters $\widehat{\gamma}_d$ and their standard errors (se), which represent the effects of household characteristics on the utilities from holding deposits relative to cash. These results follow from the specification in column (9) of Table D4 in Appendix D.1.

Table D6: Baseline Regression vs Weighted Least Squares

	(1) Baseline	(2) WLS
Deposit rate (after tax)	2.191**	3.293**
	(1.036)	(1.318)
Attitudes towards bank service	0.059***	0.044**
	(0.018)	(0.020)
Difference in ratings for cost of use	-0.101	-0.300
	(0.202)	(0.253)
Difference in ratings for ease of use	0.374	0.205
	(0.466)	(0.549)
Difference in ratings for security	0.457*	0.009
	(0.256)	(0.321)
Ratings for anonymity	-0.038**	-0.017
	(0.018)	(0.021)
Ratings for budgeting usefulness	-0.062***	-0.067***
	(0.017)	(0.022)
Fraction of online transactions	0.439	0.359
	(0.314)	(0.529)
Fraction of transactions cards unaccepted	-0.282	-0.187
	(0.181)	(0.225)
Constant	1.695***	1.346***
	(0.388)	(0.429)
Observations	4,352	4,352
Adjusted R^2	0.070	0.082
Bank Fixed Effect	Yes	Yes
Region Fixed Effect	Yes	Yes
Year Fixed Effect	Yes	Yes

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Data sources: CFM 2010–2017, MOP 2013, CANNEX 2010–2017, Government of Canada website

Note: Column (1) shows the baseline results, which are identical to column (9) in Table D4. Column (2) shows the results from a weighted regression where the sample weights are applied. Household characteristics included in each regression consist of household income, household head age, female head indicator, household head education, home ownership, household size, rural area indicator, internet access at work, attitudes towards stock market investment, feeling difficulty in paying off debt, the indicator of being behind debt obligations in the past year, as well as the bank, region, and year fixed effects. Deaton (2019, p. 72) points out that the easiest way to test the difference between the WLS and OLS estimators is to use an auxiliary regression approach. More specifically, this is done by (1) adding the sample weight and the interaction terms between each explanatory variable and the sample weight into the baseline regression and (2) using an F-test to test the joint significance of these added variables. If the null that these variables are jointly zero cannot be rejected, then there is no significant difference between WLS and OLS. Using this method, the P-value is 0.21 and hence the null cannot be rejected at the 5% level.

preference parameters $\widehat{\boldsymbol{\alpha}}$ and the effects of household characteristics $\widehat{\boldsymbol{\gamma}}^d$ are not much affected by the fixed effects, as shown in Table D7 and Table D8, respectively. The coefficients for deposit rate in columns (2) and (5) of Table D7 are smaller without the bank fixed effects, but are not statistically significant from the baseline coefficient in column (1) of Table D7.

Table D7: Comparing the Estimated Parameters $\widehat{\boldsymbol{\alpha}}$ under Different Fixed Effects

	(1) Baseline	(2) No bank FE	(3) No year FE	(4) No region FE	(5) No FE
Deposit rate	2.191**	1.227*	1.679*	2.668***	1.215*
	(1.036)	(0.739)	(0.875)	(1.032)	(0.666)
Bank service	0.059***	0.060***	0.060***	0.055***	0.057***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Cost of use	-0.101	-0.092	-0.101	-0.128	-0.122
	(0.202)	(0.200)	(0.201)	(0.202)	(0.201)
Ease/Convenience	0.374	0.373	0.363	0.212	0.185
	(0.466)	(0.466)	(0.467)	(0.464)	(0.464)
Security	0.457*	0.458*	0.452*	0.426*	0.414
	(0.256)	(0.256)	(0.256)	(0.256)	(0.255)
Anonymity	-0.038**	-0.042**	-0.038**	-0.034*	-0.039**
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Budgeting	-0.062***	-0.062***	-0.062***	-0.063***	-0.062***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Online payment	0.439	0.449	0.445	0.450	0.474
	(0.314)	(0.312)	(0.314)	(0.315)	(0.315)
Card unacceptance	-0.282	-0.374**	-0.306*	-0.244	-0.363**
	(0.181)	(0.175)	(0.180)	(0.179)	(0.174)
Constant	1.695***	1.860***	1.705***	1.984***	2.194***
	(0.388)	(0.384)	(0.374)	(0.372)	(0.355)
Observations	4,352	4,352	4,352	4,352	4,352
Adjusted R^2	0.070	0.068	0.070	0.066	0.064

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Data sources: CFM 2010–2017, MOP 2013, CANNEX 2010–2017, Government of Canada website
Note: The dependent variable is the log of deposit-to-cash ratio. FE in the column title denotes fixed effects. The baseline specification in column (1) contains bank, region, and year fixed effects. Columns (2)-(5) are identical to the baseline specification except that there are no bank fixed effects in (2), no year fixed effects in (3), no region fixed effects in (4), and no bank, year, and region fixed effects in (5). Household characteristics included in each regression consist of household income, household head age, female head indicator, household head education, home ownership, household size, rural area indicator, internet access at work, attitudes towards stock market investment, feeling difficulty in paying off debt, and the indicator of being behind debt obligations in the past year.

Table D8: Comparing the Estimated Parameters $\widehat{\gamma}^d$ under Different Fixed Effects

	Baseline		No bank FE		No year FE		No region FE		No FE	
Dislike investing in stock market	0.029**	(0.011)	0.028**	(0.011)	0.028**	(0.011)	0.028**	(0.011)	0.026**	(0.011)
Have difficulty in paying off debt	-0.075***	(0.012)	-0.075***	(0.012)	-0.074***	(0.012)	-0.074***	(0.012)	-0.073***	(0.012)
Behind debt obligations in the past year	-0.326*	(0.168)	-0.326*	(0.167)	-0.336**	(0.168)	-0.309*	(0.169)	-0.316*	(0.169)
Household head age 35–44	-0.277***	(0.106)	-0.267**	(0.106)	-0.272**	(0.106)	-0.273**	(0.106)	-0.258**	(0.107)
Household head age 45–54	-0.289***	(0.099)	-0.281***	(0.100)	-0.286***	(0.099)	-0.274***	(0.099)	-0.261***	(0.099)
Household head age 55–64	-0.223**	(0.105)	-0.204*	(0.105)	-0.211**	(0.104)	-0.217**	(0.104)	-0.187*	(0.104)
Household head age $\geqslant$ 65	-0.170	(0.122)	-0.147	(0.122)	-0.158	(0.121)	-0.154	(0.121)	-0.118	(0.120)
Household income \$15,000 - \$19,999	0.432**	(0.178)	0.444**	(0.177)	0.438**	(0.178)	0.424**	(0.180)	0.442**	(0.179)
Household income \$20,000 - \$24,999	0.476**	(0.187)	0.488***	(0.187)	0.476**	(0.187)	0.467**	(0.188)	0.480**	(0.188)
Household income \$25,000 - \$29,999	0.201	(0.185)	0.201	(0.185)	0.200	(0.185)	0.244	(0.187)	0.250	(0.187)
Household income \$30,000 - \$34,999	0.695***	(0.170)	0.693***	(0.171)	0.706***	(0.171)	0.726***	(0.171)	0.738***	(0.173)
Household income \$35,000 - \$44,999	0.648***	(0.155)	0.657***	(0.155)	0.650***	(0.155)	0.667***	(0.156)	0.682***	(0.156)
Household income \$45,000 - \$54,999	0.424***	(0.152)	0.399***	(0.152)	0.423***	(0.152)	0.439***	(0.153)	0.415***	(0.153)
Household income \$55,000 - \$59,999	0.713***	(0.184)	0.698***	(0.184)	0.715***	(0.185)	0.733***	(0.186)	0.726***	(0.186)
Household income \$60,000 - \$69,999	0.632***	(0.164)	0.607***	(0.163)	0.632***	(0.164)	0.655***	(0.164)	0.632***	(0.164)
Household income \$70,000 - \$99,999	0.768***	(0.148)	0.748***	(0.147)	0.765***	(0.147)	0.798***	(0.148)	0.779***	(0.148)
Household income \$100,000 - \$149,999	0.860***	(0.157)	0.832***	(0.156)	0.855***	(0.156)	0.906***	(0.157)	0.880***	(0.156)
Household income $\geqslant$ \$15,000	0.684***	(0.178)	0.663***	(0.177)	0.675***	(0.177)	0.734***	(0.177)	0.716***	(0.176)
Household size = 2	-0.239***	(0.084)	-0.237***	(0.084)	-0.236***	(0.084)	-0.225***	(0.084)	-0.221***	(0.084)
Household size = 3	-0.077	(0.106)	-0.077	(0.106)	-0.075	(0.106)	-0.079	(0.106)	-0.077	(0.106)
Household size $\geqslant$ 4	-0.421***	(0.108)	-0.424***	(0.108)	-0.419***	(0.108)	-0.439***	(0.108)	-0.446***	(0.108)
Grade 9-13	0.644**	(0.277)	0.588**	(0.278)	0.648**	(0.275)	0.634**	(0.274)	0.571**	(0.275)
Community College	0.664**	(0.283)	0.607**	(0.284)	0.667**	(0.282)	0.707**	(0.280)	0.653**	(0.280)
Diploma	0.759***	(0.279)	0.712**	(0.280)	0.757***	(0.278)	0.780***	(0.276)	0.732***	(0.277)
Undergraduate	0.767***	(0.280)	0.718**	(0.281)	0.767***	(0.278)	0.785***	(0.277)	0.733***	(0.277)
Post-graduate	0.918***	(0.286)	0.866***	(0.287)	0.921***	(0.284)	0.919***	(0.283)	0.865***	(0.283)
Rent a home	-0.261***	(0.078)	-0.267***	(0.079)	-0.261***	(0.078)	-0.266***	(0.078)	-0.276***	(0.079)
Household has a female head	0.283***	(0.086)	0.288***	(0.086)	0.284***	(0.086)	0.280***	(0.085)	0.287***	(0.085)
Have internet access at work/school/elsewhere	0.136*	(0.070)	0.142**	(0.070)	0.140**	(0.070)	0.159**	(0.070)	0.171**	(0.070)
Live in rural area	0.175**	(0.082)	0.181**	(0.082)	0.174**	(0.082)	0.162**	(0.082)	0.168**	(0.081)
Main financial institution (FI) is TD	0.152*	(0.091)			0.162*	(0.089)	0.178**	(0.088)		
Main FI is RBC	-0.016	(0.106)			0.003	(0.103)	-0.020	(0.106)		
Main FI is Laurentian Bank	-0.852**	(0.397)			-0.720*	(0.376)	-1.044***	(0.391)		
Main FI is not big six or Laurentian Bank	0.022	(0.092)			0.049	(0.086)	0.008	(0.091)		
Year 2011	-0.042	(0.140)	-0.041	(0.140)			-0.038	(0.140)		
Year 2012	-0.148	(0.133)	-0.147	(0.132)			-0.142	(0.133)		
Year 2013	0.004	(0.124)	-0.005	(0.124)			0.008	(0.125)		
Year 2014	0.073	(0.129)	0.055	(0.128)			0.089	(0.129)		
Year 2015	0.003	(0.134)	-0.032	(0.131)			0.018	(0.134)		
Year 2016	0.111	(0.139)	0.069	(0.135)			0.135	(0.140)		
Year 2017	-0.023	(0.144)	-0.066	(0.140)			-0.002	(0.144)		
Quebec	0.308**	(0.133)	0.298**	(0.132)	0.316**	(0.133)				
Ontario	0.418***	(0.126)	0.461***	(0.125)	0.425***	(0.126)				
Prairies	0.508***	(0.137)	0.539***	(0.137)	0.517***	(0.137)				
British Columbia	0.560***	(0.140)	0.592***	(0.140)	0.570***	(0.140)				
Observations	4,352		4,352		4,352		4,352		4,352	
Adjusted R^2	0.070		0.068		0.070		0.066		0.064	

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Data sources: CFM 2010–2017, MOP 2013, CANNEX 2010–2017, Government of Canada website

Note: The dependent variable is the log of deposit-to-cash ratio. The estimated bank fixed effects (indicators of TD, RBC, Laurentian Bank, and banks other than the big six or Laurentian Bank), region fixed effects (indicators of Quebec, Ontario, Prairies, and British Columbia), and year fixed effects are shown in the table. FE in the column title denotes fixed effects. The baseline specification contains bank, region, and year fixed effects. The remaining specifications are identical to the baseline specification except that there are no bank fixed effects in columns "No bank FE", no year fixed effects in columns "No year FE", no region fixed effects in columns "No region FE", and no bank, year, and region fixed effects in columns "No FE". The table shows the estimated parameters $\widehat{\gamma}_d$, which represent the effects of household characteristics on the utilities from holding deposits relative to cash. Product attributes are included in each specification and the estimated parameters can be found in the corresponding specification in Table D7.

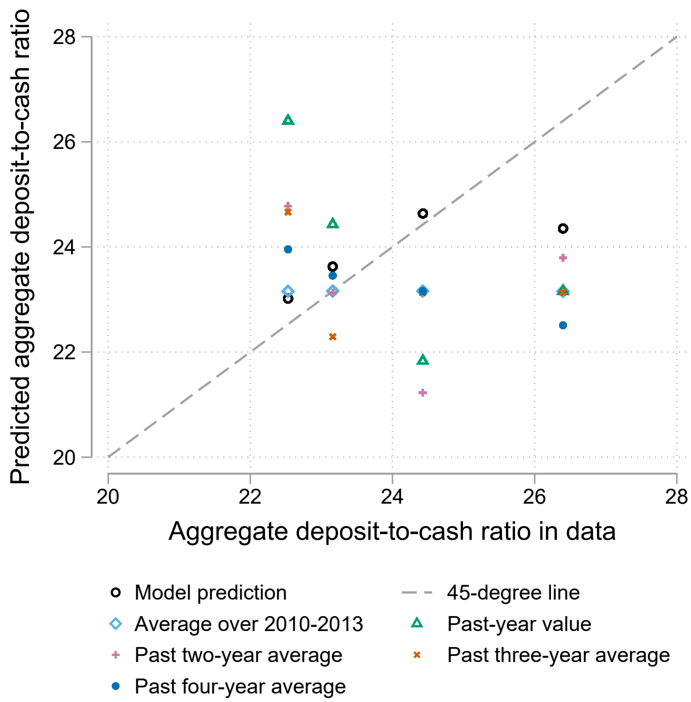
D.3 Out-of-sample Prediction

The adjusted R squared in Table D4 is only around 0.07 and the correlation between the predicted deposit-to-cash ratio and the data values is around 0.28, which indicates that it is difficult to have precise predictions for each household due to a lot of variability in the deposit-to-cash ratios across households. Since the counterfactual analyses focus on the aggregate CBDC share instead of aiming to precisely predict each household's CBDC holding, I check how well the model can predict the aggregate deposit-to-cash ratio.

More specifically, I estimate the model using data from 2010–2013 and then predict the aggregate deposit-to-cash ratio during 2014–2017 using the estimated parameters excluding those for the year fixed effects, since the year dummies for 2010–2013 are not in the prediction sample of 2014–2017. The results are robust to excluding the year fixed effects from the estimation sample of 2010–2013 all together.

Figure D5 plots the predicted values of the aggregate deposit-to-cash ratio and different naive estimates against the corresponding data values in each year from 2014 to 2017. I find that these model-predicted values outperform the naive estimates based on different ways of averaging the past data values, as shown in Figure D5. The naive estimates are often negatively correlated with the data values. Besides, the root mean squared errors of the naive estimates (i.e., using simple average over 2010–2013, past-year value, or past two-/three-/four-year average to predict the aggregate deposit-to-cash ratios from 2014 to 2017) are around 63–169% larger than those of the model-predicted values, depending on which naive estimate is used.

Figure D5: Model-Predicted Aggregate Deposit-to-Cash Ratio vs. Naive Estimates



Data sources: CFM 2010–2017, MOP 2013, CANNEX 2010–2017, Government of Canada website
Note: The graph plots the predicted values of the aggregate deposit-to-cash ratio based on the model and different naive estimates against the corresponding data values for years from 2014 to 2017. Each point is associated with a given year. The model-predicted values are calculated based on the estimated parameters (excluding those estimates of the year fixed effects) from the subsample of 2010 to 2013. The naive estimates (i.e., average over 2010–2013, past-year value, past two-/three-/four-year average) use the data values of the aggregate deposit-to-cash ratio in the past to predict the aggregate deposit-to-cash ratio for each year from 2014 to 2017. The dashed line is a 45-degree line.

E Counterfactual Results

Section E.1 provides more details on how CBDC demand is measured in this paper. Section E.2 shows the results on the predicted demand for CBDC. Section E.3 discusses the predicted CBDC demand under the nested logit model. Section E.4 shows the detailed results on the impact of each CBDC attribute on the percentage change in CBDC demand. Section E.5 studies three design scenarios for CBDC that are frequently discussed and the impacts of CBDC design changes. Section E.6 studies the holdings of CBDC by different demographic groups.

As robustness checks, Section E.7 shows the estimation results on how preference parameters can differ across demographic groups and conducts counterfactual analyses using different sets of parameters that are estimated separately from subsamples. Section E.8 discusses the potential changes in the attributes of existing products after CBDC issuance.

E.1 Constructing the Measure of CBDC Demand

In this paper, CBDC demand is measured by the aggregate CBDC share s_{cbdc}, which is the ratio of CBDC in the total household holdings of liquid assets $w = \sum_i w_i$ in a given year:

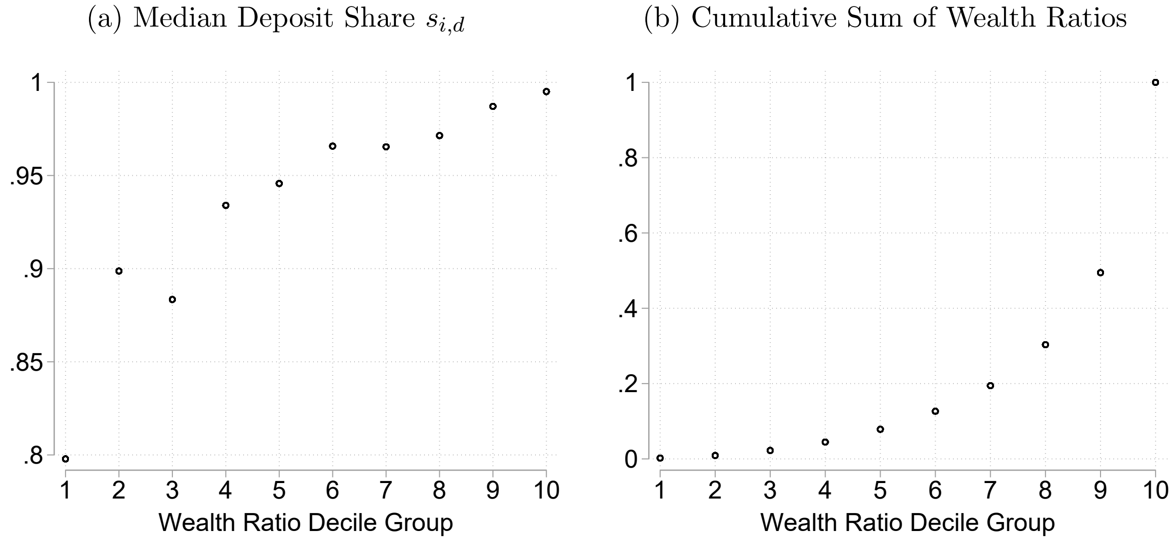
$$s_{cbdc} = \frac{\sum_i s_{i,cbdc} w_i}{w} = \sum_i \frac{w_i}{w} s_{i,cbdc}$$

This is equivalent to a weighted sum of the predicted CBDC share $s_{i,cbdc}$ across all households and each household's wealth ratio $\frac{w_i}{w}$ acts as a weight.

I use the aggregate CBDC share s_{cbdc} to measure the demand for CBDC because of two reasons. First, s_{cbdc} shows the potential take-up of CBDC at an aggregate level and provides a direct reference of how much CBDC to issue. Although the aggregate CBDC share is driven by the wealthiest households with high weights $\frac{w_i}{w}$, this is not a concern in this case because the asset shares $s_{i,j}$ chosen by the wealthiest are very similar to the asset share choices by the majority of households, as shown in Figure E6.

Second, the model can predict the aggregate asset shares well. As shown in Table E9, the predicted aggregate cash (deposit) share is identical to the aggregate cash (deposit) share in the data. In contrast, the predicted average cash (deposit) share does not exactly match the average cash (deposit) share in the data, since the model cannot capture the full distribution of the asset shares across households. However, this does not affect the baseline results since I focus on the aggregate CBDC share.

Figure E6: Median Asset Share and Cumulative Weight by Decile Groups of Wealth Ratio



Data sources: CFM 2017
Note: Figure (a) plots the median deposits share $s_{i,d}$ within each decile group of the wealth ratio $\frac{w_i}{w}$. It shows that the wealthiest households in the top decile group have similar median deposit shares compared to the majority of households from the other decile groups. Since cash share is constructed by one minus the deposit share, the graph on median cash share is not shown here. Figure (b) plots the cumulative sum of the wealth ratios from each decile group. I first calculate $\sum_i \frac{w_i}{w}$ across households within each decile group of the wealth ratio to get the total weight of each decile group, and then sum over these within-group total weights to plot the cumulative sum. It shows that the liquid assets held by the top 10% of households account for around 50% of the total household liquid assets.

Table E9: Aggregate and Average Asset Shares in Data vs Prediction

	Data	Model Predicted Value
Aggregate cash share	0.04	0.04
Average cash share	0.12	0.05
Aggregate deposit share	0.96	0.96
Average deposit share	0.88	0.95

Data sources: CFM 2010–2017, MOP 2013, CANNEX 2010–2017, Government of Canada website
Note: The table compares the data values and the model predicted values of the aggregate asset shares and average asset shares in year 2017. The model predicted values are calculated using the demand parameters estimated in the sample of 2010–2017 under the baseline analysis. Aggregate share of an asset j is computed as the weighted sum of asset shares across all households, i.e., $s_j = \sum_i \frac{w_i}{w} s_{i,j}$, where the weight $\frac{w_i}{w}$ is household i's liquid assets over all households' liquid assets. Average asset share is computed as $\bar{s}_j = \sum_i \frac{1}{H} s_{i,j}$, where H denotes the number of all households and an equal weight of $\frac{1}{H}$ is applied to all households.

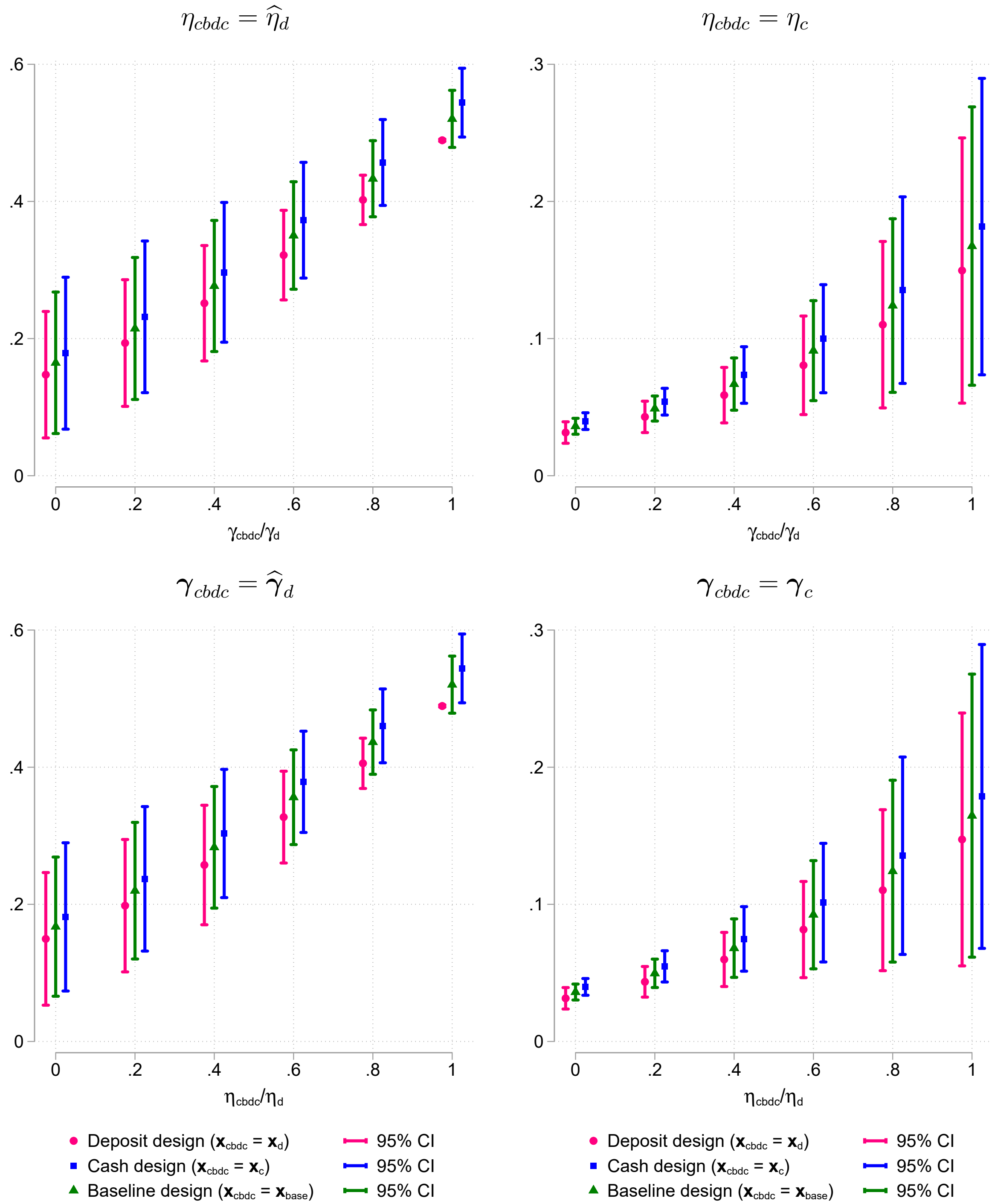
E.2 Predicted Demand for CBDC under Logit Model

Figure E7 shows how the aggregate CBDC shares s_{cbdc} change with the assumptions of the CBDC-specific effects (i.e., $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc}). The upper panel plots s_{cbdc} against the values of $\boldsymbol{\gamma}_{cbdc}/\widehat{\boldsymbol{\gamma}}_d$ conditional on two different values of the CBDC fixed effect η_{cbdc}. The lower panel plots s_{cbdc} against the values of $\eta_{cbdc}/\widehat{\eta}_d$ conditional on the effects $\boldsymbol{\gamma}_{cbdc}$ of household characteristics on the utilities from CBDC.

Figure E7 shows that the two components of the CBDC-specific effects, i.e., $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc}, are equally important in determining the potential level of CBDC demand. The upper panel shows that as $\boldsymbol{\gamma}_{cbdc}$ approaches $\widehat{\boldsymbol{\gamma}}_d$, the aggregate CBDC share increases from around 16% to 52% (4% to 17%) conditional on $\eta_{cbdc} = \widehat{\eta}_d$ ($\eta_{cbdc} = \eta_c$). Similarly, the lower panel shows that as η_{cbdc} approaches $\widehat{\eta}_d$, the aggregate CBDC share increases from around 17% to 52% (4% to 16%), conditional on $\boldsymbol{\gamma}_{cbdc} = \widehat{\boldsymbol{\gamma}}_d$ ($\boldsymbol{\gamma}_{cbdc} = \boldsymbol{\gamma}_c$).

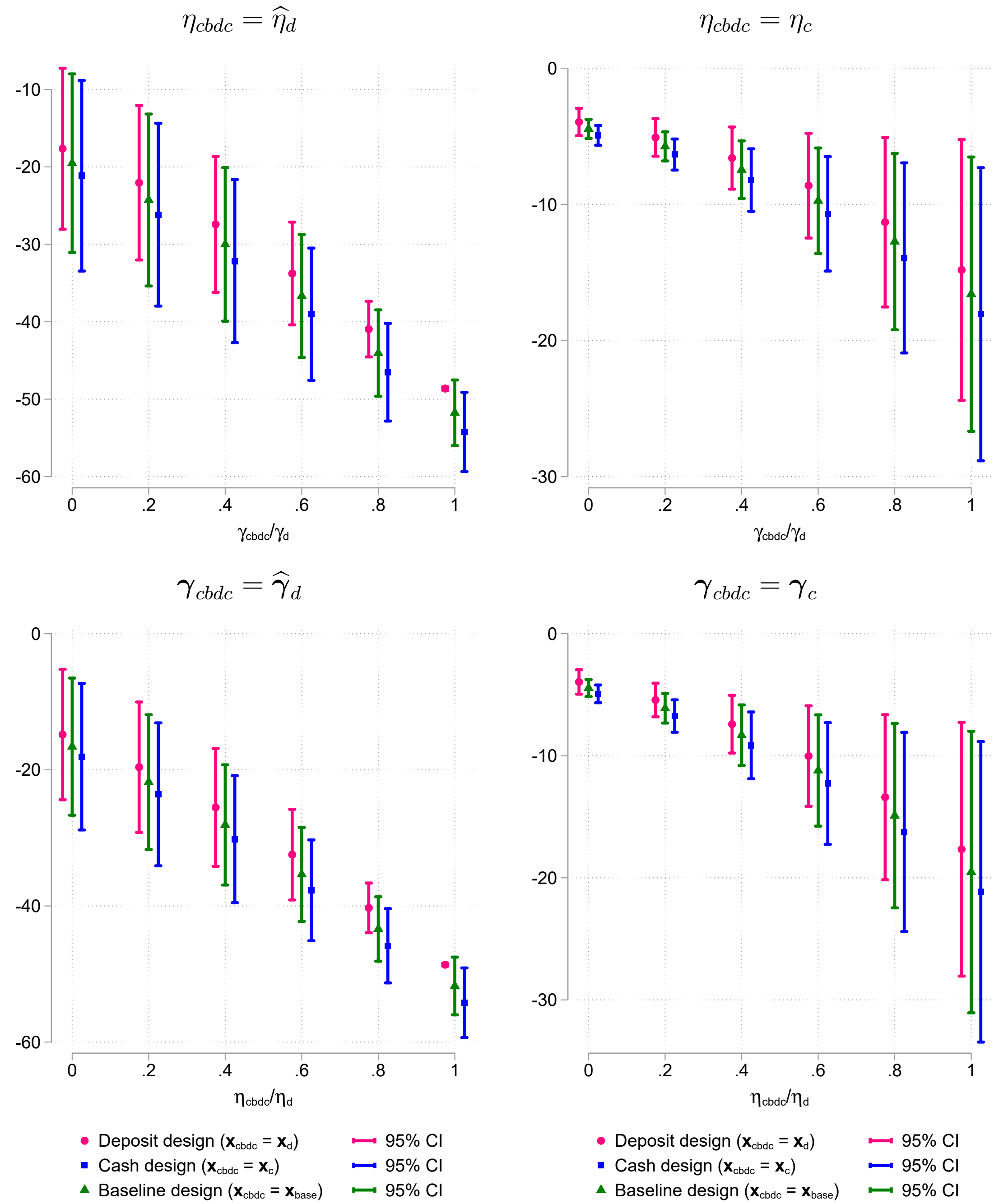
Figure E8 shows how the mean percentage change in deposit demand varies with the assumptions of the CBDC-specific effects (i.e., $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc}). Under the logit model, the demand for CBDC draws proportionally from deposits and cash, so the percentage drops in deposit and cash demand are identical. As can be seen from Figure E8, when the CBDC-specific effects change from being cash-like to being deposit-like, the crowding-out effects on the demand for deposits are larger due to a higher CBDC demand. When CBDC-specific effects are cash-like (i.e., $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc} both take the normalised value for cash, which is zero), the mean percentage drop in deposits and cash across households is around 4%. When CBDC-specific effects are deposit-like (i.e., $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc} both take the estimated value for deposits, so that $\boldsymbol{\gamma}_{cbdc}/\widehat{\boldsymbol{\gamma}}_d$ equals one), the mean percentage drop in deposits and cash across households is around 52%.

Figure E7: Aggregate CBDC Shares for Different Assumptions on CBDC-specific Effects



Note: The graphs in the upper (lower) panel plot the aggregate CBDC shares against different values of γ_{cbdc} (η_{cbdc}) as a fraction of the estimated parameters $\widehat{\gamma}_d$ ($\widehat{\eta}_d$) conditional on the value of η_{cbdc} (γ_{cbdc}). In each graph, three different designs for CBDC are plotted, that is, when CBDC attributes $\boldsymbol{x}_{cbdc}$ are identical to deposit attributes ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_d$), cash attributes ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_c$), or a mixture of both ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_{base}$). The standard errors for calculating the 95% confidence intervals are computed using the delta method.

Figure E8: Mean Percentage Change in Deposits for Different CBDC-specific Effects



Note: The graphs in the upper (lower) panel plot the mean percentage change in deposits relative to the deposit holding before CBDC issuance for different values of γ_{cbdc} (η_{cbdc}) as a fraction of the estimated parameters $\widehat{\gamma}_d$ ($\widehat{\eta}_d$), conditional on different values of η_{cbdc} (γ_{cbdc}). Since deposits and cash are substituted proportionally into CBDC under the logit model, these graphs also represent the mean percentage changes in cash. In each graph, three different designs for CBDC are plotted, that is, when CBDC attributes $\boldsymbol{x}_{cbdc}$ are identical to deposit attributes ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_d$), cash attributes ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_c$), or a mixture of both ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_{base}$). The standard errors for calculating the 95% confidence intervals are computed using the delta method.

E.3 Predicted Demand for CBDC under Nested Logit Model

Under the logit model, CBDC is treated as a distinct product in the sense that households possess a unique set of unobserved idiosyncratic preferences for CBDC. In other words, there are no common factors driving the unobserved idiosyncratic preferences for different products. This assumption is relaxed in this section, so that CBDC can be a closer substitute for deposits or cash due to the correlated idiosyncratic preferences. This section examines to what extent the predictions from the logit model are robust to the correlated unobserved utilities across products.

Figure E9 plots the aggregate CBDC shares against different levels of correlation ranging from 0 to 0.99, assuming the unobserved utility for CBDC is correlated with that for deposits (left panel) or cash (right panel). A higher correlation between the unobserved utilities for CBDC and deposits (cash) implies greater substitutability between CBDC and deposits (cash). When the correlation is zero, the predictions are identical to those based on the logit model. Each graph plots the aggregate CBDC shares under the deposit design, the cash design, and the baseline design.

There are three main implications from Figure E9. First, the predicted aggregate CBDC shares are robust to a wide range of correlation coefficients. When the correlation is below 0.8, the level changes in the aggregate CBDC shares across different levels of correlation are small, conditional on a given CBDC design.

Second, the impact of the correlation on the aggregate CBDC share depends on the utility difference between CBDC and its closer substitute, as discussed in Section 2.2.2 of the paper. For example, under the deposit design in the first graph, CBDC and deposits have the same observed utility, as both the design of CBDC and the CBDC-specific effects are identical to those of deposits. In this case, as ρ_{d_cbdc} increases, cash is reduced by less as CBDC demand draws more than proportionally from deposits. As a consequence, the remaining asset share that can be allocated to CBDC and deposits is smaller, which leads to a lower CBDC share. This effect can be reversed (reinforced) by the substitution between CBDC and deposits when CBDC has a higher (lower) observed utility than deposits. Under the cash design or the baseline design, CBDC has a higher observed utility than deposits due to better anonymity and budgeting usefulness features, so a higher ρ_{d_cbdc} that makes them more substitutable can lead to greater substitution from deposits into CBDC and hence a higher aggregate CBDC share.

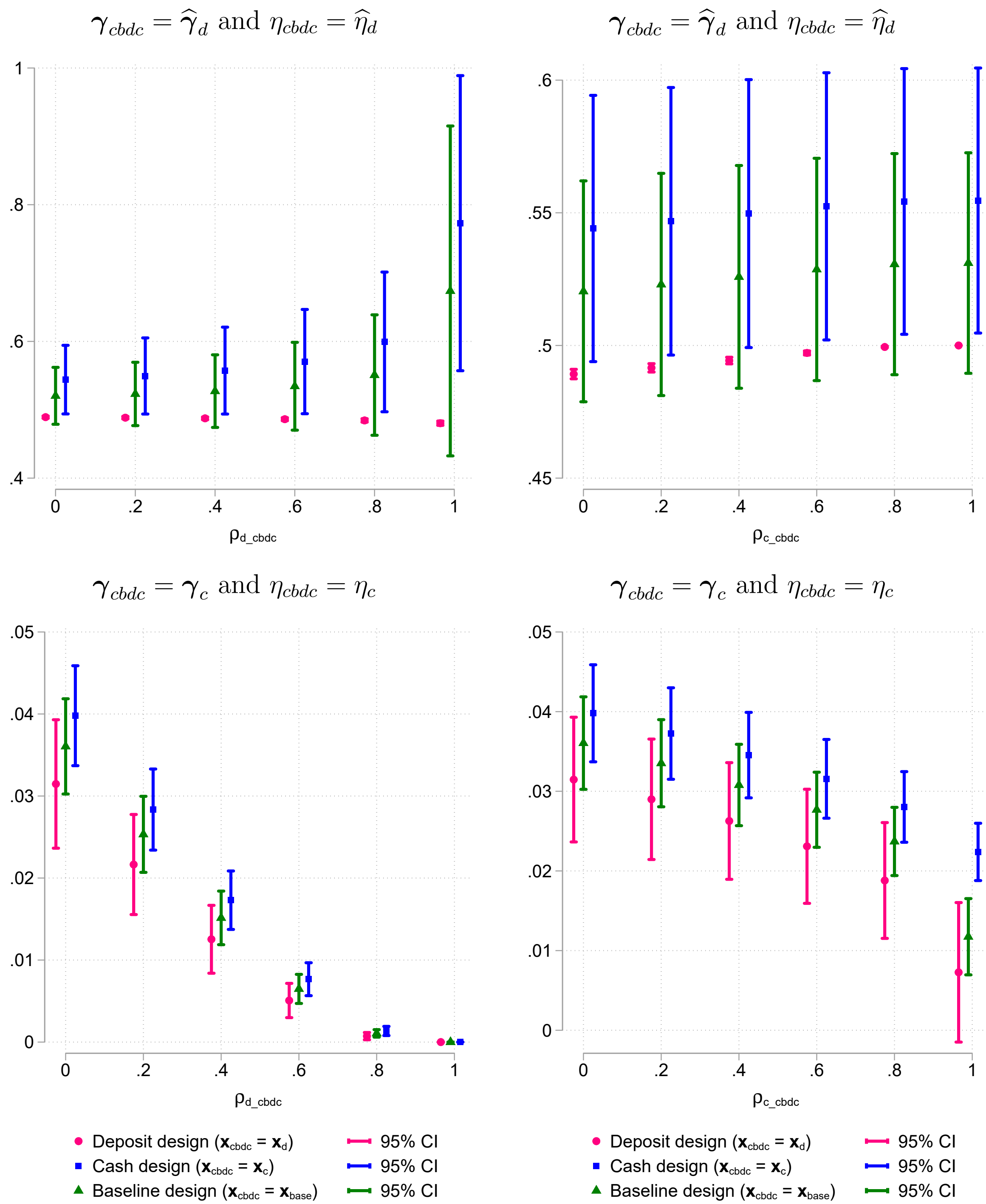
In contrast, in the bottom right graph, CBDC with the deposit design or the baseline design has a lower observed utility than that with the cash design, so a higher ρ_{c_cbdc} leads to greater substitution from CBDC into cash and larger drops in the CBDC shares compared to the drop under the cash design. Apart from the design, the CBDC-specific effects can also lead to an observed utility difference. The bottom left graph shows that when CBDC has a much lower observed utility than deposits due to the CBDC-specific effects being cash-like (i.e., $\boldsymbol{\gamma}_{cbdc} = \boldsymbol{\gamma}_c$ and $\eta_{cbdc} = \eta_c$), there is greater substitution from CBDC to deposits and the aggregate CBDC share approaches zero as ρ_{d_cbdc} increases.

Third, the correlation ρ_{c_cbdc} between the unobserved utilities for CBDC and cash has a much smaller impact compared to ρ_{d_cbdc}. The right panel of Figure E9 shows that the level changes in aggregate CBDC shares are small even when ρ_{c_cbdc} approaches one. This is because households only hold a small fraction of their liquid assets in cash. Hence, even if CBDC has a much higher observed utility than cash due to the CBDC-specific effects being deposit-like (i.e., $\boldsymbol{\gamma}_{cbdc} = \widehat{\boldsymbol{\gamma}}_d$ and $\eta_{cbdc} = \widehat{\eta}_d$), the greater substitution from cash into CBDC as ρ_{c_cbdc} increases would not add much extra demand for CBDC, as shown in the top right graph.

Similar to the logit model, the crowding-out effects on the demand for deposits and cash depend a lot on CBDC-specific effects. Suppose CBDC has a baseline design and is a closer substitute to deposits. The left panels of Figure E10 and E11 show that when CBDC-specific effects are cash-like, deposit and cash demand would only be reduced by around 0–4%. In contrast, when CBDC-specific effects are deposit-like, the demand for deposits (cash) can be crowded out by around 52–70% (15–52%), as ρ_{d_cbdc} increases from 0 to 0.99.

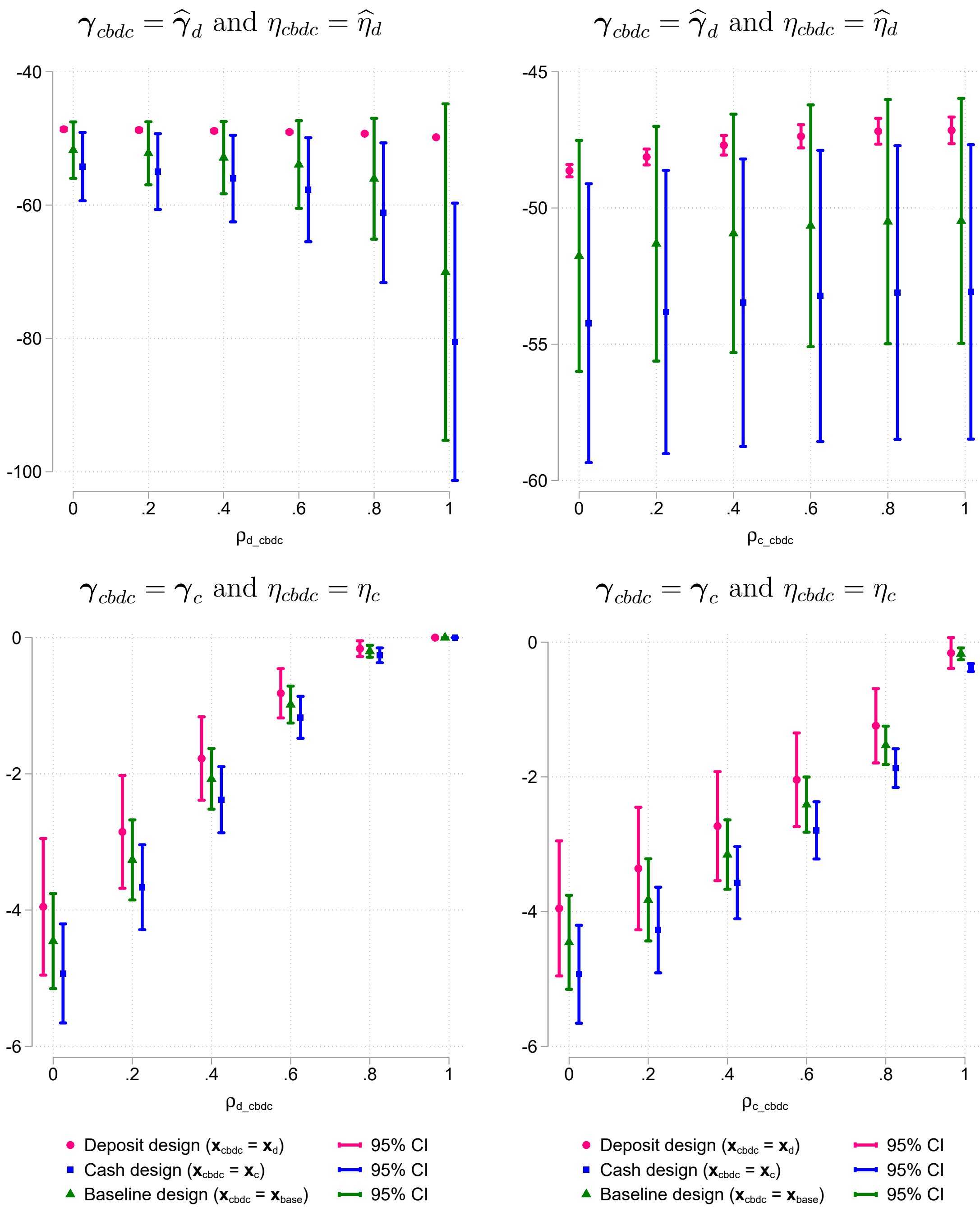
When CBDC is a closer substitute to cash, the crowding out on deposit demand is robust to changes in the correlation ρ_{c_cbdc}, whereas the crowding out on cash demand is more sensitive to ρ_{c_cbdc}, as shown in the right panels of Figure E10 and E11. Intuitively, the latter is because people only hold a small amount of cash, so even a small level change can be a large percentage change. As ρ_{c_cbdc} increases from 0 to 0.99, implying that CBDC and cash become more substitutable, deposit (cash) demand would be reduced by 50–52% (52–100%) when CBDC-specific effects are deposit-like, and 0–4% (4–26%) when CBDC-specific effects are cash-like.

Figure E9: Aggregate CBDC Shares for Different Degrees of Substitutability



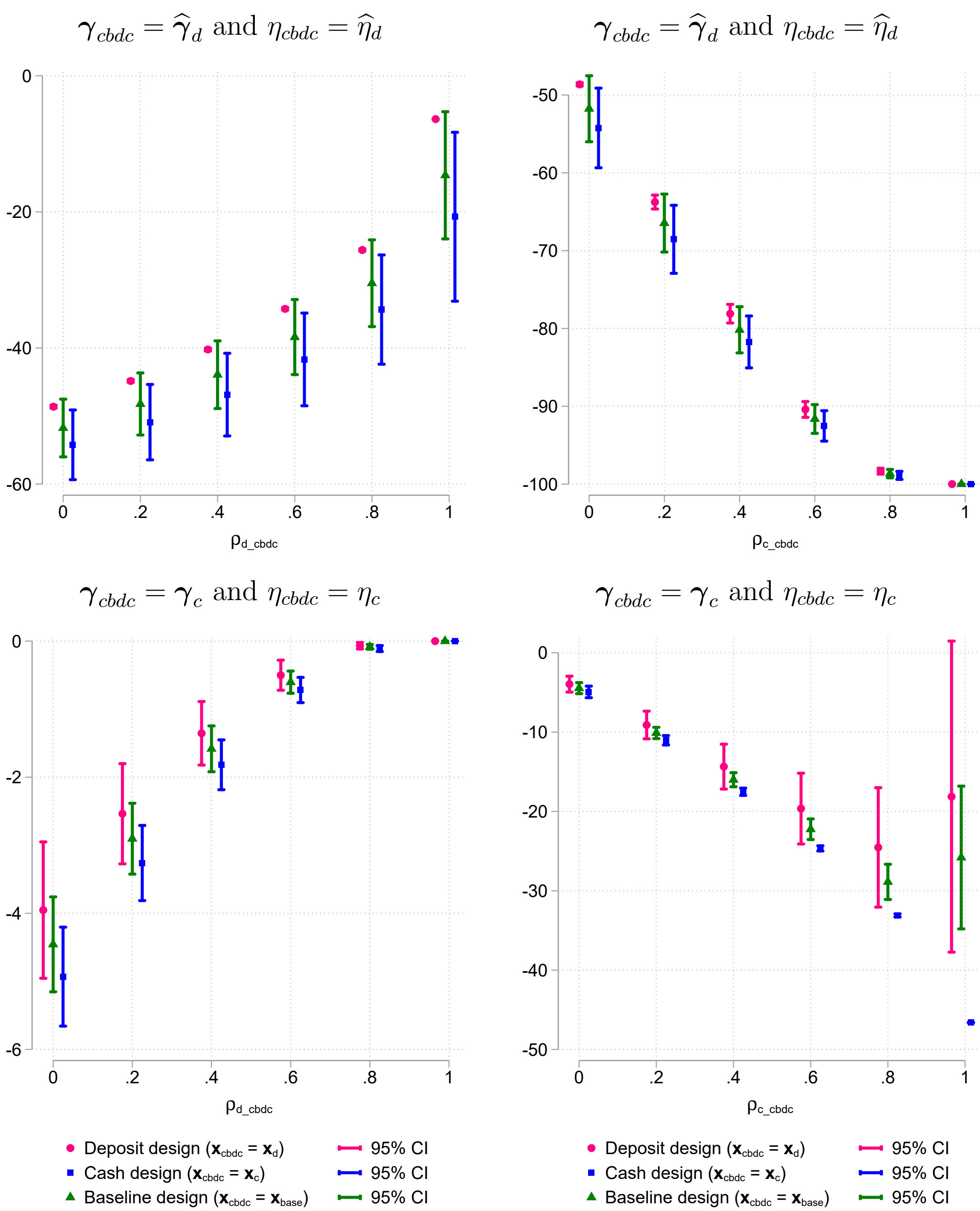
Note: The left (right) panel plots the aggregate CBDC shares against different levels of correlation ρ_{d_cbdc} (ρ_{c_cbdc}) between the unobserved utilities for CBDC and deposits (cash), conditional on different values of γ_{cbdc} and η_{cbdc}. The correlation coefficient ranges from 0–0.99. A higher correlation ρ_{d_cbdc} (ρ_{c_cbdc}) implies greater substitutability between CBDC and deposits (cash). In each graph, three different designs for CBDC are plotted, that is, when CBDC attributes $\boldsymbol{x}_{cbdc}$ are identical to deposit attributes ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_d$), cash attributes ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_c$), or a mixture of both ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_{base}$). The standard errors for calculating the 95% confidence intervals are computed using the delta method.

Figure E10: Mean Percentage Change in Deposits for Different Degrees of Substitutability



Note: The graphs in the left (right) column plot the mean percentage change in deposit holding relative to that before the CBDC issuance for different levels of correlation $\rho_{d\_cbdc}(\rho_{c\_cbdc}) \in [0, 0.99]$ between the unobserved utilities for CBDC and deposits (cash), conditional on different values of $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc}. A higher correlation $\rho_{d\_cbdc}(\rho_{c\_cbdc})$ implies greater substitutability between CBDC and deposits (cash). In each graph, three different designs for CBDC are plotted, that is, when CBDC attributes $\boldsymbol{x}_{cbdc}$ are identical to deposit attributes ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_d$), cash attributes ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_c$), or a mixture of both ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_{base}$). The standard errors for calculating the 95% confidence intervals are computed using the delta method.

Figure E11: Mean Percentage Change in Cash for Different Degrees of Substitutability



Note: The graphs in the left (right) column plot the mean percentage change in cash holding relative to that before the CBDC issuance for different levels of correlation $\rho_{d\_cbdc}(\rho_{c\_cbdc}) \in [0, 0.99]$ between the unobserved utilities for CBDC and deposits (cash), conditional on different values of γ_{cbdc} and η_{cbdc}. A higher correlation $\rho_{d\_cbdc}(\rho_{c\_cbdc})$ implies greater substitutability between CBDC and deposits (cash). In each graph, three different designs for CBDC are plotted, that is, when CBDC attributes $\boldsymbol{x}_{cbdc}$ are identical to deposit attributes ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_d$), cash attributes ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_c$), or a mixture of both ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_{base}$). The standard errors for calculating the 95% confidence intervals are computed using the delta method.

E.4 The Impacts of CBDC Design Attributes

This section shows the predicted impact of each CBDC attribute based on both the baseline logit demand model and the nested logit model. The impact of a design attribute tends to be larger under the nested logit model. Intuitively, when CBDC and deposits are closer substitutes for example, any attribute change will lead to greater substitution between the two. Hence, the predictions based on the logit model can be viewed as more conservative estimates.

Note that Table 3 in the paper only shows the point estimates of the percentage changes in aggregate CBDC shares s_{cbdc} in response to the change in each important attribute under the logit model. Table E10 shows the impacts of all CBDC design attributes and compares the baseline results under the logit model with the predictions under two different nested logit models, each with a high level of correlation between the unobserved utilities of deposits and CBDC ($\rho_{d\_cbdc} = 0.75$) or between the unobserved utilities of cash and CBDC ($\rho_{c\_cbdc} = 0.75$).

Table E10: Percentage Changes in CBDC Demand when CBDC Attribute Changes

Design attribute	Change in attribute relative to baseline design	% change in s_{cbdc} logit model	$\rho_{d\_cbdc} = 0.75$	$\rho_{c\_cbdc} = 0.75$
Interest rate	0% → 0.1%	10 to 23	18 to 54	10 to 38
Budgeting usefulness	0.7 → 0	-7 to -14	-13 to -26	-7 to -21
Anonymity	0.7 → 0	-5 to -10	-9 to -20	-5 to -16
Bundling of bank service	0 → 1	4 to 8	7 to 16	4 to 13
Cost of use	cash rating → debit card rating	-1 to -1	-1 to -3	-1 to -2
Ease of use	cash rating → debit card rating	-1 to -1	-1 to -2	-1 to -2
Security	cash rating → debit card rating	-1 to -2	-2 to -7	-1 to -4
Online payment capability	1 → 0	-1 to -1	-1 to -2	-1 to -2
Merchant unacceptance	0 → 0.25	-3 to -7	-6 to -13	-3 to -10

Note: The table shows the percentage changes in aggregate CBDC shares s_{cbdc} in response to a change in CBDC attribute based on the logit model and two different nested logit models. The second column describes the change in CBDC attribute relative to its attribute under the baseline design. The last three columns show the predicted percentage changes in s_{cbdc} in response to the attribute change under different model assumptions, i.e., logit model under the baseline analysis, nested logit model where CBDC and deposits are closer substitutes due to correlated unobserved utilities $\rho_{d\_cbdc} = 0.75$, and nested logit model where CBDC and cash are closer substitutes with $\rho_{c\_cbdc} = 0.75$. Point estimates of the percentage changes are reported in the table. The lower (upper) bound estimate in each cell of the last three columns refers to the prediction based on the assumption that CBDC-specific effects are deposit-like (cash-like).

The rest of this section discusses each of the attribute in more details. For each feature, I show the point estimates of the predicted percentage changes in aggregate CBDC shares s_{cbdc} together with the confidence intervals. Since ρ_{c_cbdc} has a smaller impact compared to ρ_{d_cbdc} as shown in Table E10, I only compare the baseline results based on the logit model and the results from the nested logit model with a high correlation ρ_{d_cbdc} between the unobserved utilities of deposits and CBDC.

CBDC Interest Rate

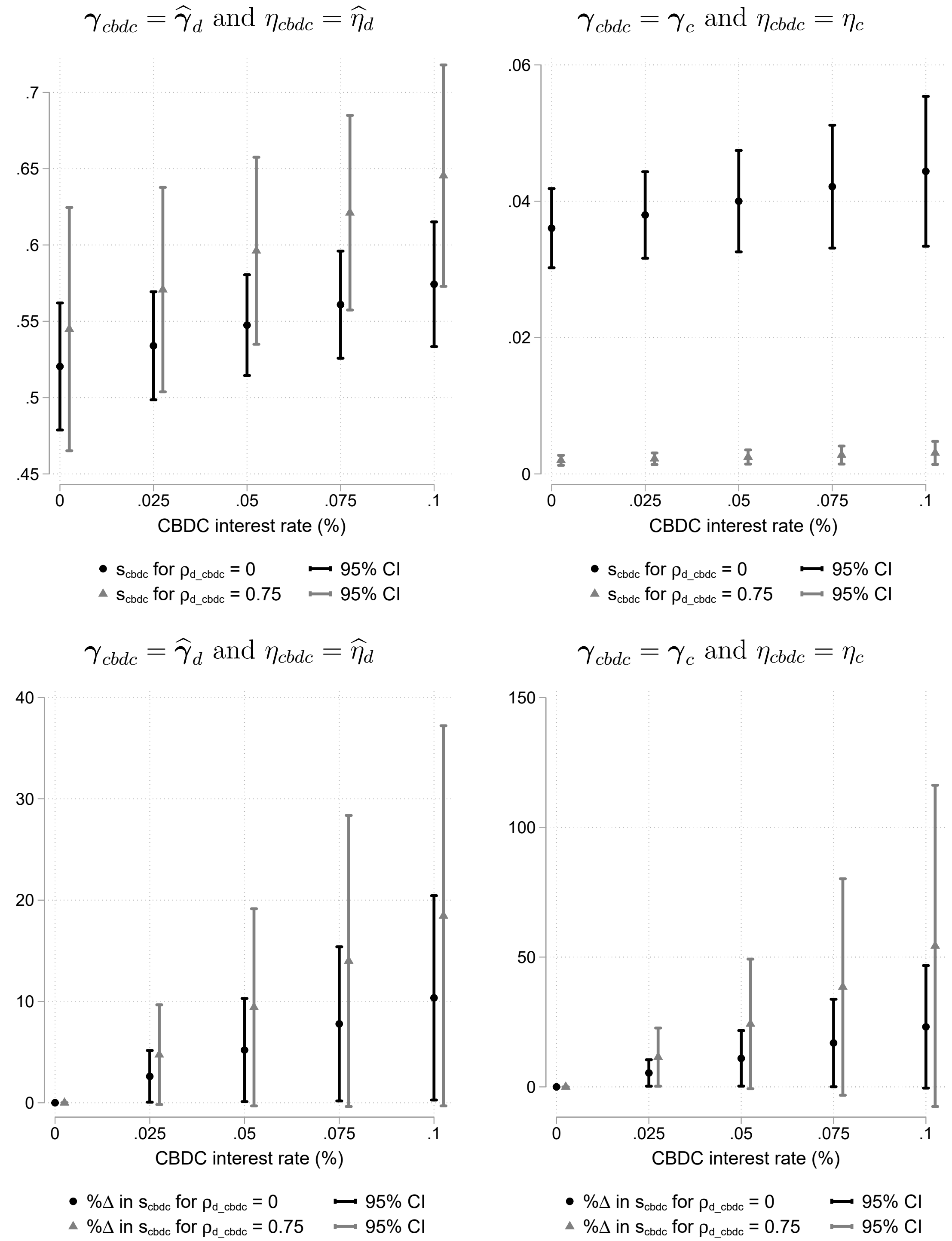
Figure E12 shows how changes in the CBDC interest rate would impact the aggregate CBDC shares (upper panel) and the percentage changes in aggregate CBDC shares relative to those under the baseline design (lower panel), conditional on the CBDC-specific effects (i.e., $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc}) and the correlation ρ_{d_cbdc} between the unobserved utilities for CBDC and deposits. The range 0–0.1% is chosen because the median (75th percentile) deposit rate after tax is around 0.08% (0.1%) across households during 2010–2017.

The upper panel of Figure E12 shows that as the CBDC rate increases from 0% to 0.1%, the aggregate CBDC share increases from 52% to 57% (3.6% to 4.4%), when CBDC-specific effects are deposit-like (cash-like) under the logit model. As can be seen, the predicted levels of CBDC demand differ a lot depending on CBDC-specific effects. To summarize the impacts of the CBDC interest rate across different assumptions on CBDC-specific effects, I look at the percentage changes in the aggregate CBDC shares relative to the shares under the baseline design in the lower panel.

As shown in the lower panel of Figure E12, when CBDC is non-interest-bearing as in the baseline design, there is a zero percentage change in the aggregate CBDC share. Based on the logit model where $\rho_{d\_cbdc} = 0$, as the CBDC rate rises to 0.1%, the aggregate CBDC share increases by around 10% (23%) if CBDC-specific effects are deposit-like (cash-like). The 0.1 percentage point increase in CBDC rate is a large change as most households face a post-tax deposit rate that is below 0.1%. When the correlation is high (e.g., $\rho_{d\_cbdc} = 0.75$), the percentage changes in aggregate CBDC shares are larger due to the greater substitutability between deposits and CBDC that enlarges the impact of the attribute change.

The range of 10% to 23% is much narrower compared to the range for the predicted level of CBDC demand, implying that the percentage changes in CBDC demand depend much less on CBDC-specific effects. This is because by looking at the percentage changes in demand in response to the attribute change, the level effects can be largely canceled out. For the rest of this section, I focus on the impacts of design attributes on the percentage changes in CBDC demand.

Figure E12: The Impact of Rate of Return on CBDC Demand



Note: The graph plots the aggregate CBDC share s_{cbdc} (upper panel) and the percentage change $\%\Delta$ in the aggregate CBDC share s_{cbdc} relative to the baseline value (lower panel) for different levels of CBDC interest rate ranging from 0% to 0.1%, conditional on different values of γ_{cbdc} and η_{cbdc}. In each graph, two different levels of the correlation ρ_{d_cbdc} between the unobserved utilities for CBDC and deposits are plotted. The standard errors for calculating the 95% confidence intervals are computed using the delta method.

CBDC Anonymity and Usefulness for Budgeting

Figure E13 shows the impacts of anonymity and budgeting usefulness on the percentage changes in aggregate CBDC shares. The point of zero (one) on the x-axis refers to the level of anonymity or budgeting usefulness for deposits (cash). Under the baseline design, CBDC is assumed to achieve 70% of the cash anonymity and budgeting usefulness. Relative to the baseline design, if the anonymity level of CBDC reduces to the deposit anonymity level, the aggregate CBDC share would drop by around 5–10% under the logit model, where the range is due to different assumptions on CBDC-specific effects (i.e., γ_{cbdc} and η_{cbdc}). Under the nested logit model where the correlation ρ_{d_cbdc} is assumed to be 0.75, the aggregate CBDC share would drop by around 9–20%. If CBDC under the baseline design could achieve the cash anonymity, that is, the level of anonymity increases from 0.7 to 1, the aggregate CBDC share would increase by around 2–5% (4–10%) when $\rho_{d\_cbdc} = 0$ (0.75).

Budgeting usefulness has a larger impact than anonymity. Relative to the baseline design where CBDC can achieve 70% of the cash budgeting usefulness, if CBDC becomes less useful for budgeting like deposits, its aggregate share would drop by around 7–14% under the logit model where $\rho_{d\_cbdc} = 0$. If CBDC becomes as useful for budgeting as cash, its aggregate share would increase by around 3–7% when $\rho_{d\_cbdc} = 0$.

Bundling of Bank Services

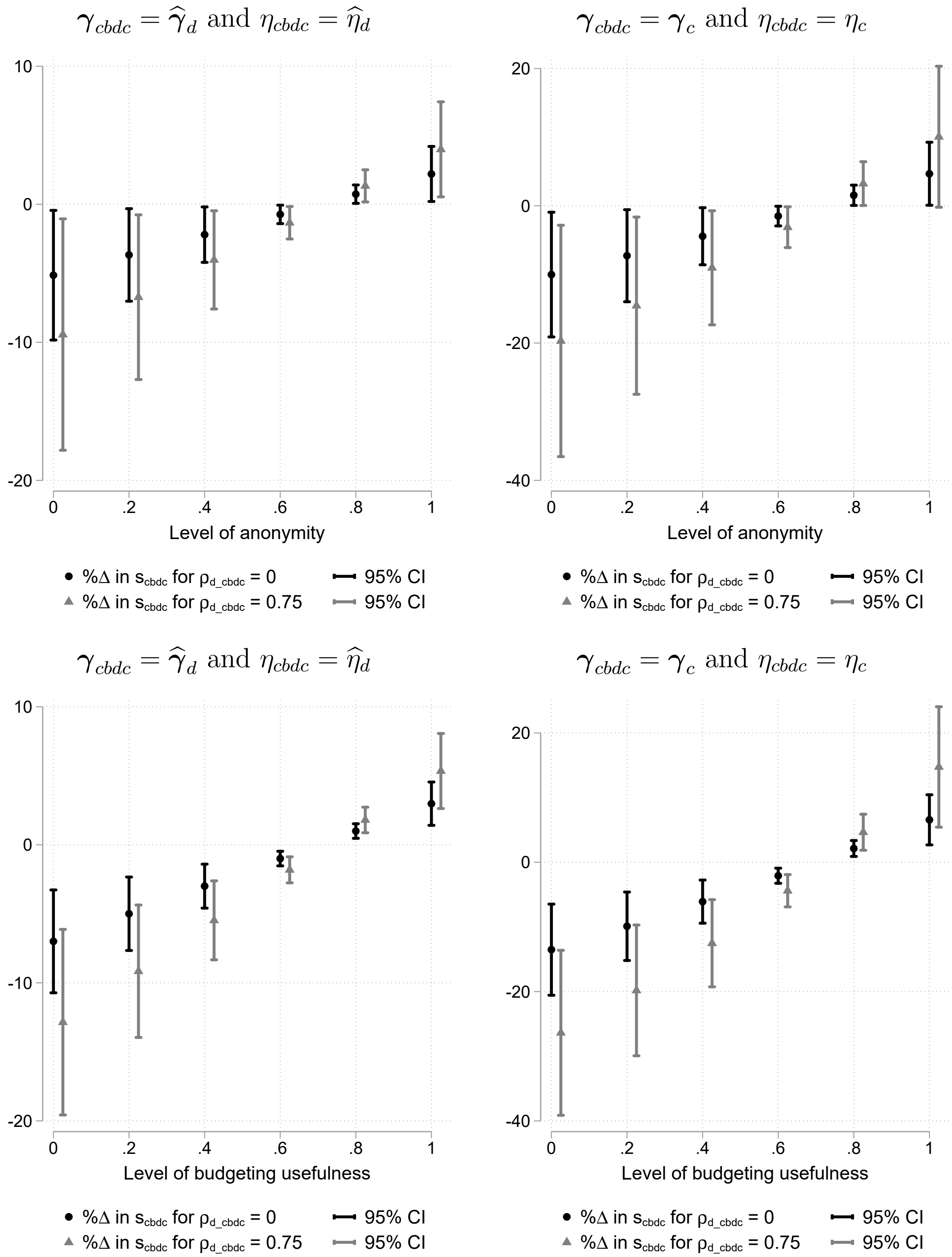
Figure E14 shows the impact of the bundling of the financial planning advice service. Under the baseline design, CBDC is assumed to have the same level of bundling as cash. If CBDC has a higher degree of bundling like deposits, then its aggregate share would increase by around 4–8% relative to the share under the baseline design, depending on CBDC-specific effects. When $\rho_{d\_cbdc} = 0.75$, the changes in CBDC demand are larger while the confidence intervals are also wider.

Cost, Ease of Use, and Security

Figure E15 shows the changes in the aggregate CBDC share when the cost, ease of use, and security features of CBDC are each measured by the ratings for a given payment instrument. Apart from the most frequently used payment instruments (i.e., cash, debit cards, and credit cards), I also look at the ratings for mobile payment apps and prepaid cards because CBDC may be accessed through a smartphone or a physical payment card. Hence, the ratings for these payment instruments may be better proxies for people's perceptions towards how easy or secure it is when using CBDC to make payments.

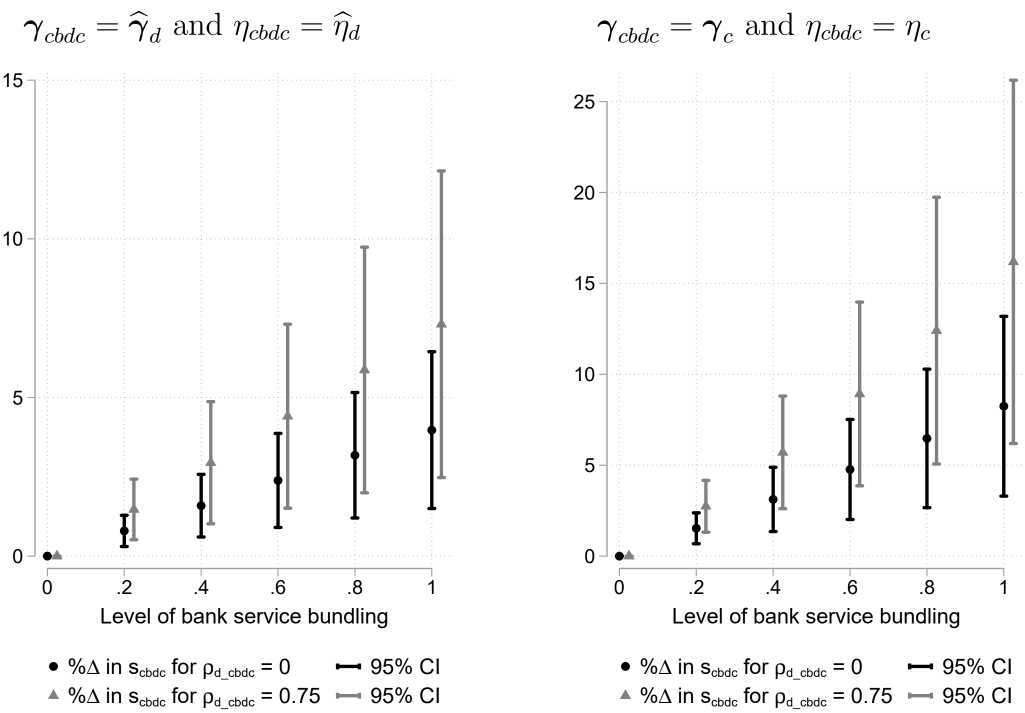
Under the baseline design, CBDC is perceived to be as cheap, easy, and secure to use as

Figure E13: The Impacts of Anonymity and Budgeting Usefulness on CBDC Demand



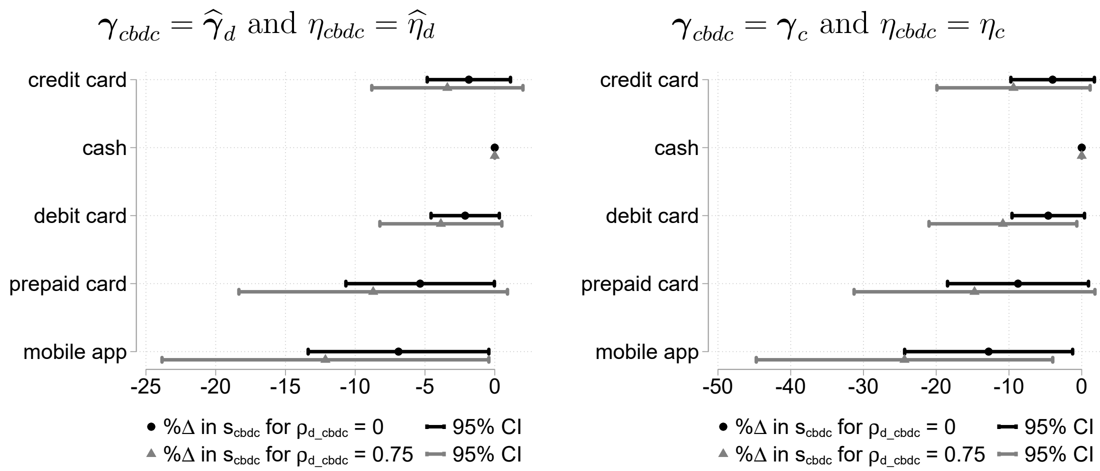
Note: The graph plots the percentage change %Δ in the aggregate CBDC share s_{cbdc} relative to the share under the baseline design against different levels of anonymity (upper panel) and usefulness for budgeting (lower panel), conditional on different values of γ_{cbdc} and η_{cbdc}. The point of zero (one) on the x-axis refers to the level of anonymity or budgeting usefulness for deposits (cash). In each graph, two different levels of the correlation ρ_{d_cbdc} between the unobserved utilities for CBDC and deposits are plotted. The standard errors for calculating the 95% confidence intervals are computed using the delta method.

Figure E14: The Impact of Bank Service Bundling on CBDC Demand



Note: The graph plots the percentage change %Δ in the aggregate CBDC share s_{cbdc} relative to the share under the baseline design against different levels of bank service bundling, conditional on different values of $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc}. The point of zero (one) on the x-axis refers to the level of bundling for cash (deposits). In each graph, two different levels of the correlation ρ_{d_cbdc} between the unobserved utilities for CBDC and deposits are plotted. The standard errors for calculating the 95% confidence intervals are computed using the delta method.

Figure E15: The Impacts of Cost, Ease, and Security on CBDC Demand



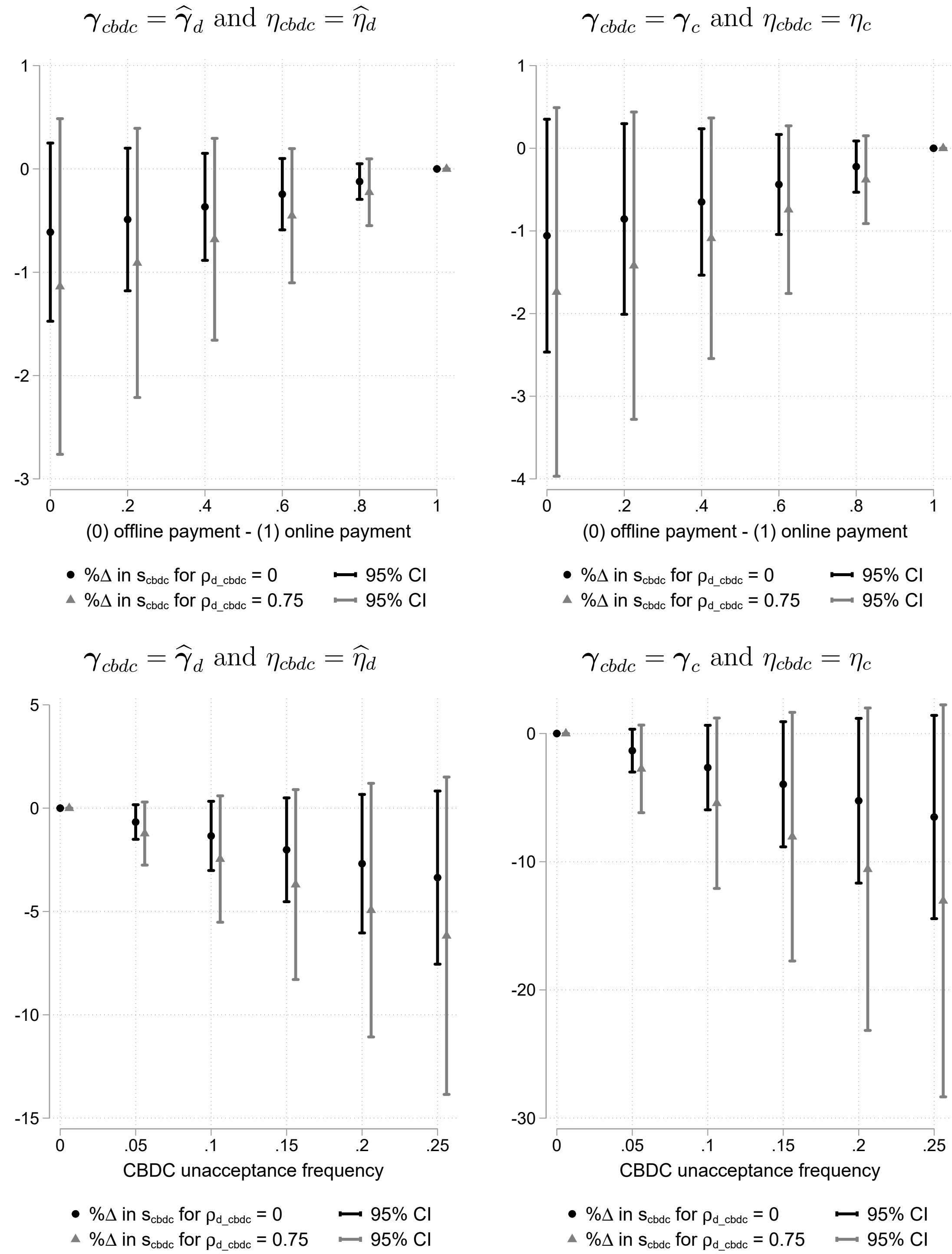
Note: The graph plots the percentage change %Δ in the aggregate CBDC share s_{cbdc} relative to the share under the baseline design for different levels of cost of use, ease of use, and security, conditional on different values of γ_{cbdc} and η_{cbdc}. The y-axis refers to the ratings for different payment instruments that are used to measure the cost, ease, and security of using CBDC to make payments. In each graph, two different levels of the correlation ρ_{d_cbdc} between the unobserved utilities for CBDC and deposits are plotted. The standard errors for calculating the 95% confidence intervals are computed using the delta method.

cash. If these payment features of CBDC change from cash ratings to debit card or credit card ratings, the changes in the aggregate CBDC share are very small, as shown in Figure E15. However, if these CBDC features are measured by the ratings for prepaid cards (mobile apps), then the aggregate CBDC share would drop by around 5–9% (7–13%) under the logit model where $\rho_{d\_cbdc} = 0$, depending on CBDC-specific effects. This is because people perceive prepaid cards or mobile apps to be much less easy and secure to use than cash, while their perceptions towards debit or credit cards are relatively similar to those for cash, as shown in Table C2 in Appendix C.5.

Other Features of CBDC

The impacts of online purchase capability and unacceptance rate are shown in Figure E16. The upper panel of Figure E16 shows that relative to the baseline design where CBDC can be used for online purchases, losing this feature only reduces its aggregate share by around 1%. This small impact is partly because only around 12% of people shopped online for one or more transactions from the three-day shopping diary in MOP 2013. Those who do not shop online will not obtain any utility from this feature, so this online feature does not contribute much to the aggregate CBDC share. The lower panel shows that relative to the baseline design where CBDC is assumed to be universally accepted by merchants, if all households find that there is a 25% probability that CBDC is unaccepted, then the aggregate CBDC share would drop by around 3–7% under the logit model. Note that this is a large change in the acceptance rate of CBDC because the mean and median unacceptance rates across households are around 0.06 and 0, respectively.

Figure E16: The Impacts of Online Purchase Capability and Unacceptance Rate



Note: The graphs plot the percentage changes $\%\Delta$ in the aggregate CBDC share s_{cbdc} relative to the share under the baseline design against different degrees of online purchase capability (upper panel) and CBDC unacceptance frequency (lower panel), conditional on different values of γ_{cbdc} and η_{cbdc}. In each graph, two different levels of the correlation ρ_{d_cbdc} between the unobserved utilities for CBDC and deposits are plotted. The standard errors for calculating the 95% confidence intervals are computed using the delta method.

E.5 Applications to CBDC Design Scenarios

This section shows the impacts of design changes on CBDC demand, focusing on three designs that are frequently discussed. Table E11 shows the CBDC attributes under three different design scenarios, where CBDC is designed to capture some prominent features of a cryptocurrency, the Bahamian Sand Dollar, or a synthetic CBDC, respectively. The three designs differ in terms of anonymity, bundling of bank services, cost, ease of use, and security. For features such as the rate of return, budgeting usefulness, and merchant acceptance, it is more difficult to ascertain their relative levels without enough information, so I set them equal across the designs for simplicity of interpretation.

Table E11: CBDC Attributes under Different Design Scenarios

CBDC design	Return	Bundling	Cost	Ease	Security	Anonymity	Budgeting	Online	Acceptance
Cryptocurrency	0	0	very low	mobile app	mobile app	1	0	1	1
Sand Dollar	0	0	very low	mobile app prepaid card	mobile app prepaid card	0.2	0	1	1
Synthetic CBDC	0	1	debit card	debit card	debit card	0	0	1	1

Note: The table shows the product attributes of CBDC when designing CBDC to capture certain features of a cryptocurrency, the Bahamian Sand Dollar, or a synthetic CBDC, respectively. Cost, ease of use, and security are each measured by the ratings for mobile payment applications, prepaid cards, or debit cards, depending on the design. For the Sand Dollar, I use the average ratings for mobile apps and prepaid cards to measure its ease and security features. "Very low" means that the cost takes the lowest rating of one (i.e., very low cost) on a Likert scale of 1–5.

Across the three designs, only the cryptocurrency design is able to reach the full degree of cash anonymity, where anonymity refers to the separation of users' identities from their transactions. Unlike bitcoin that is pseudonymous, some cryptocurrencies such as Monero, Zcash, and Dash can better conceal users' identities by shielding the transaction information and thus making it difficult to analyze the transaction patterns to back out the user identity. Although it is unlikely for a central bank to issue a fully anonymous CBDC, it is still useful to compare a "central bank cryptocurrency" (Berentsen and Schar, 2018; Bech and Garratt, 2017) design with other designs.

I assume that a CBDC with a cryptocurrency design would be perceived as a very low-cost payment instrument because some cryptocurrencies can have very low transaction fees. For example, during the past year up to August 2021, the average transaction fee for Dash is often below 0.005 US dollars and even the highest point is below 0.04 US dollars.[2] I use the ratings for mobile payment apps to measure the ease and security of using CBDC with the cryptocurrency design to make payments as it can be accessed via mobile wallets.

[2]The average transaction fees can be found on the website: https://bitinfocharts.com/comparison/dash-transactionfees.html#1y.

The synthetic CBDC proposed in Adrian and Mancini-Griffoli (2019) is not a CBDC and is similar to deposits provided by a narrow bank that are fully backed by reserves at the central bank (BIS, 2020). Hence, the design for the synthetic CBDC is similar to the deposit design, where the debit card ratings are used to measure the cost, ease-of-use, and security features. In addition, CBDC under this design is assumed to have the same level of bank service bundling and anonymity as deposits.

The Sand Dollar is the world's first nationwide CBDC issued by the central bank of the Bahamas. Although it is not designed to replicate the anonymity feature of cash, it tends to have a slightly higher degree of anonymity than deposits due to the tiered know-your-customer requirements. For example, the Tier I wallet with a holding limit of $500 does not require an official ID, which is designed for the unbanked, non-residents, or visitors.[3] Since the unbanked account for around 20% of the adult population in the Bahamas (IMF, 2019, p. 13) and these people would likely use the Tier I wallet, I assume that the Sand Dollar can achieve 20% of the cash anonymity. According to the official website, the Sand Dollar has zero transaction fees for individuals, so I assume it would be perceived as a very low cost payment instrument. Since the digital wallet for the Sand Dollar can be accessed via a mobile phone or a physical smart card, I use the average ratings for mobile payment apps and prepaid cards to measure the ease and security features.

Table E12: Percentage Changes in CBDC Demand when CBDC Design Changes

Design	Cryptocurrency	Sand Dollar	Synthetic CBDC
Cryptocurrency	0	-6 to -10	-1 to -2
Sand Dollar	6 to 11	0	6 to 9
Synthetic CBDC	1 to 2	-6 to -8	0

Note: The table shows the percentage changes in CBDC demand when the CBDC design changes from each design in the first column to each design in the first row under the logit model. The three designs represent the scenarios where CBDC is designed to replicate certain features of a cryptocurrency, the Bahamian Sand Dollar, or a synthetic CBDC, respectively. The first (second) number in each cell refers to the prediction based on the assumption that CBDC-specific effects are deposit-like (cash-like).

Table E12 shows the percentage change in the aggregate CBDC share when changing from each design in the first column to each design in the first row under the logit model. As can be seen, when changing from the cryptocurrency design to the Sand Dollar design with

[3]Details for the Tier I wallet can be found from https://www.sanddollar.bs/individual and who can use it can be found from https://www.sanddollar.bs/getinvolved.

a much lower level of anonymity, CBDC demand would drop by around 6–10%, depending on different assumptions for CBDC-specific effects. Although the synthetic CBDC design has better features in terms of the bundling of bank services, ease of use, and security,[4] this is still not enough to compensate for its low anonymity level. As a result, moving from the cryptocurrency design with a high level of anonymity to the synthetic CBDC design would reduce the CBDC demand by around 1–2%. In contrast, when changing from the Sand Dollar design with a low level of anonymity to the synthetic CBDC design, the CBDC demand would increase by 6–9%.

Under the nested logit model, the impacts of the design changes on CBDC demand would be larger. For instance, a higher correlation between the unobserved utilities for CBDC and deposit implies that CBDC and deposit are more substitutable, so any changes in CBDC designs would lead to greater substitution between them and hence larger changes in CBDC demand. When the correlation is high (i.e., $\rho_{d\_cbdc} = 0.75$), the magnitude of the changes in CBDC demand is roughly twice as large.

[4] As shown in Table C2 in Appendix C.5, more people perceive debit cards to be easy and secure to use compared to mobile apps or prepaid cards.

E.6 CBDC Demand across Different Demographic Groups

This section studies how CBDC holdings differ across social demographic groups if CBDC were present during the period of 2014–2017. Using a sample over a few years is to ensure that there are sufficient observations to calculate the mean predicted CBDC holding within each demographic group.

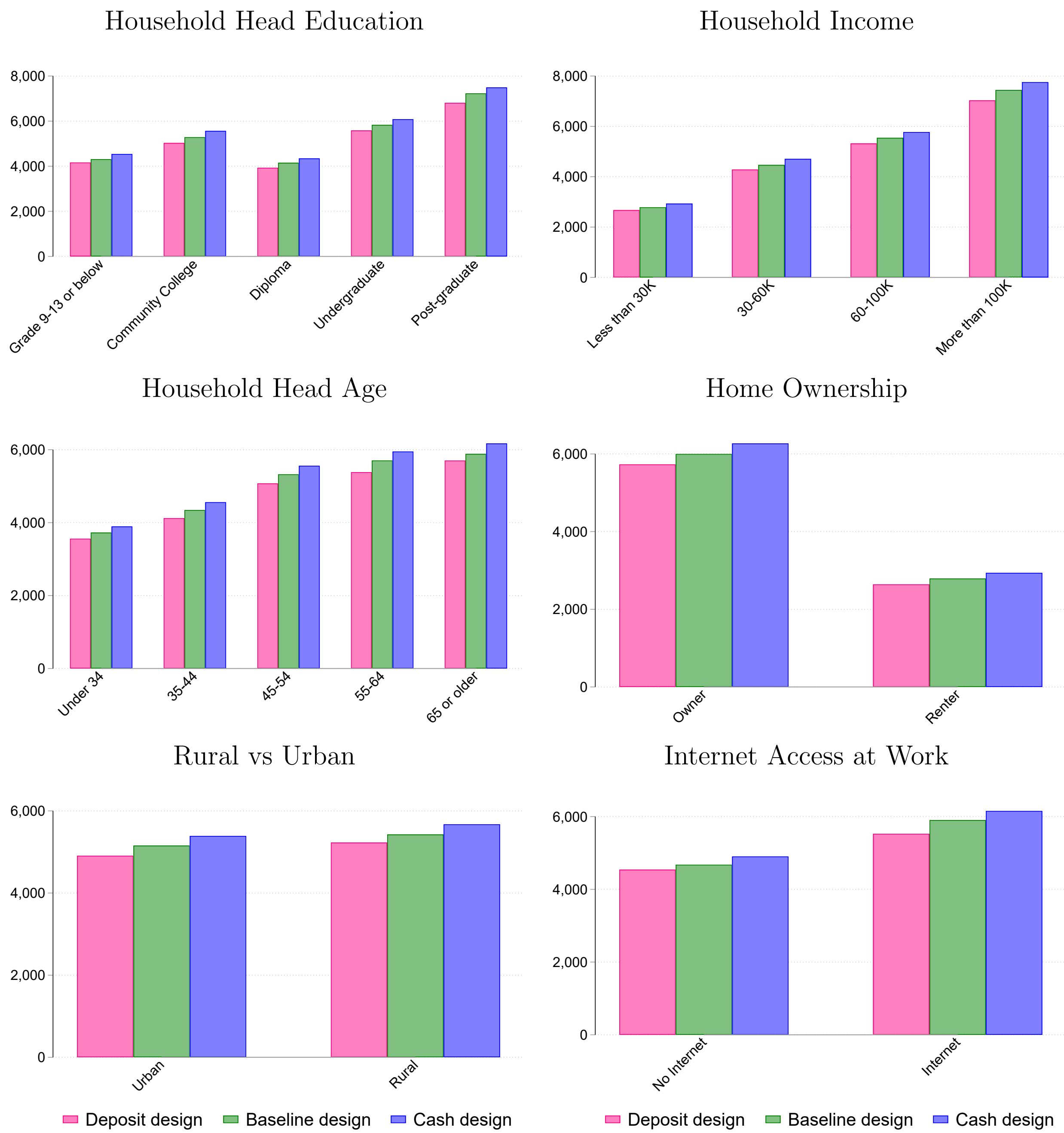
Figure E17 shows the unweighted mean predicted CBDC holdings in Canadian dollars across different demographic groups based on the logit model. Within each demographic group, the predicted holdings under three different designs are shown, that is, the deposit design, the cash design, and the baseline design.

Figure E17 shows that households with higher education, higher income, older age, or home ownership tend to hold more CBDC on average. In contrast, the differences in CBDC holdings between groups living in rural vs. urban areas or having vs. not having internet access are small. These patterns are similar across the three CBDC designs, although the magnitude of the CBDC holdings differs slightly across designs. Under the cash (deposit) design, CBDC holdings across different groups are slightly higher (lower) compared to the baseline design, since the cash (deposit) design is better (worse) in terms of anonymity and budgeting usefulness features.

Since the observed utility for CBDC depends on both the design and the CBDC-specific effects (i.e., $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc}), the patterns being similar across the designs indicates that they are driven by the CBDC-specific effects. Figure E17 assumes that CBDC-specific effects are deposit-like (i.e., $\boldsymbol{\gamma}_{cbdc} = \widehat{\boldsymbol{\gamma}}_d$ and $\eta_{cbdc} = \widehat{\eta}_d$), implying that households tend to perceive CBDC to be closer to deposits. In this case, if households in a given demographic group prefer to hold more deposits, they would also want to hold more CBDC. Figure E18 shows that the types of households that tend to hold more CBDC in Figure E17 also hold more deposits during 2014–2017 in the CFM data. Similarly, Figure E19 shows that households with older age, higher income, or home ownership, tend to hold more cash in the data. I find that when assuming CBDC-specific effects are cash-like (i.e., $\boldsymbol{\gamma}_{cbdc} = \boldsymbol{\gamma}_c$ and $\eta_{cbdc} = \eta_c$), those groups also tend to hold more CBDC in this case, as shown in Figure E20.

The patterns in Figure E17 are robust to different time periods (or years) except for the level of education and are robust to different ways of summarizing the CBDC holdings (e.g., median or weighted mean holdings). This section examined the holdings of CBDC instead of the shares because the latter is entangled with the effects of wealth. For example, households in older age groups tend to hold more CBDC, but they also have more liquid assets. If the two effects cancel out each other, the CBDC shares between the older and younger age groups should be similar. If this wealth effect dominates, households in older age groups that hold more CBDC balances can have lower CBDC shares. I find that when

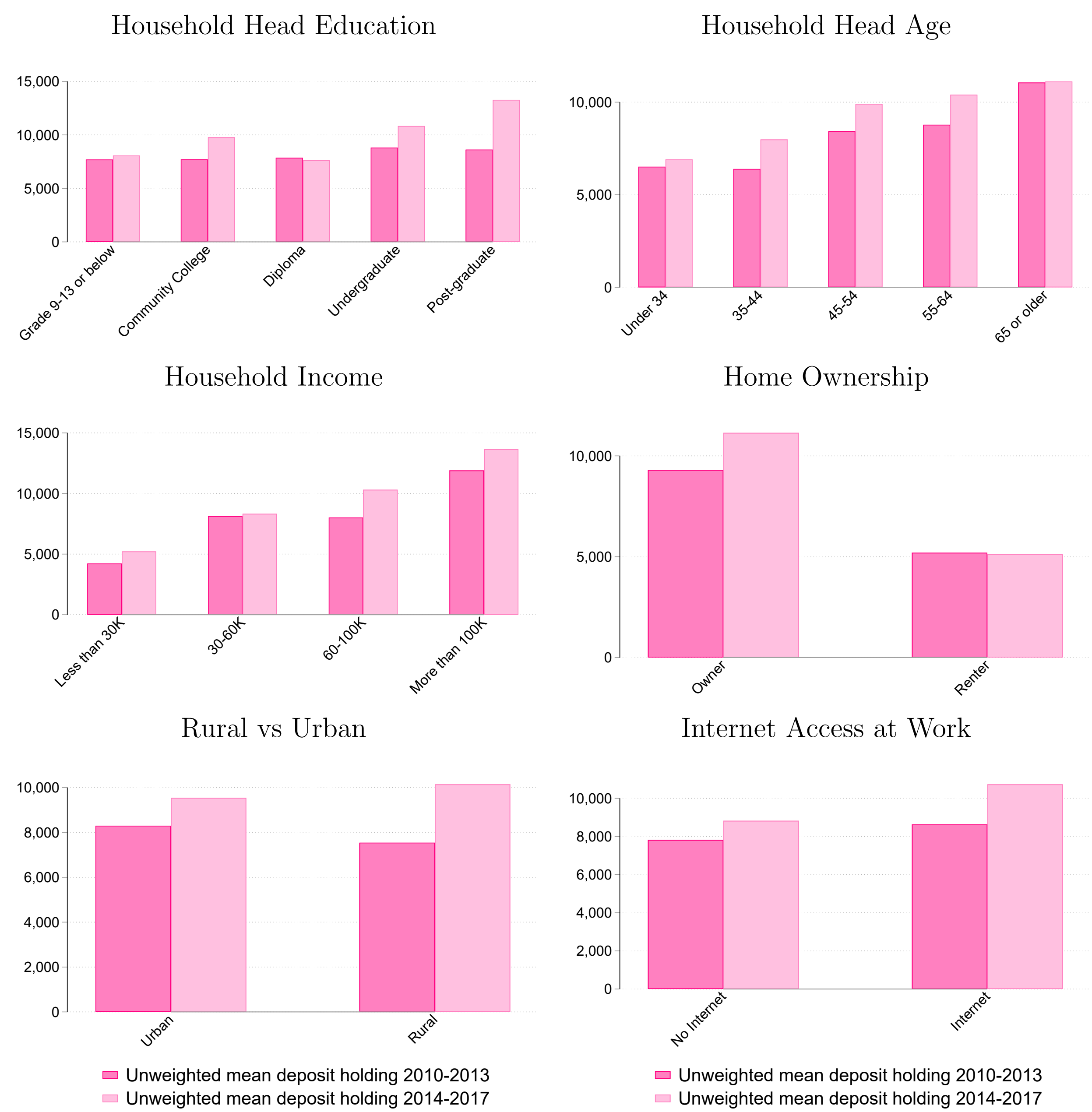
Figure E17: CBDC holdings in Canadian Dollars across Demographic Groups



Note: The bar charts show the unweighted mean predicted CBDC holdings across households and over the period of 2014–2017 for different demographic groups. For a given demographic group, the predicted CBDC holdings under three different designs are plotted. The CBDC holdings are predicted from the logit model based on the assumption that CBDC-specific effects are deposit-like. The predicted CBDC holdings are deflated by CPI in each year.

assuming that CBDC-specific effects are deposit-like, there is not much difference in CBDC shares across different demographic groups. In contrast, when assuming that CBDC-specific effects are cash-like, households with higher education, higher income, home ownership, or internet access at work tend to have lower CBDC shares.

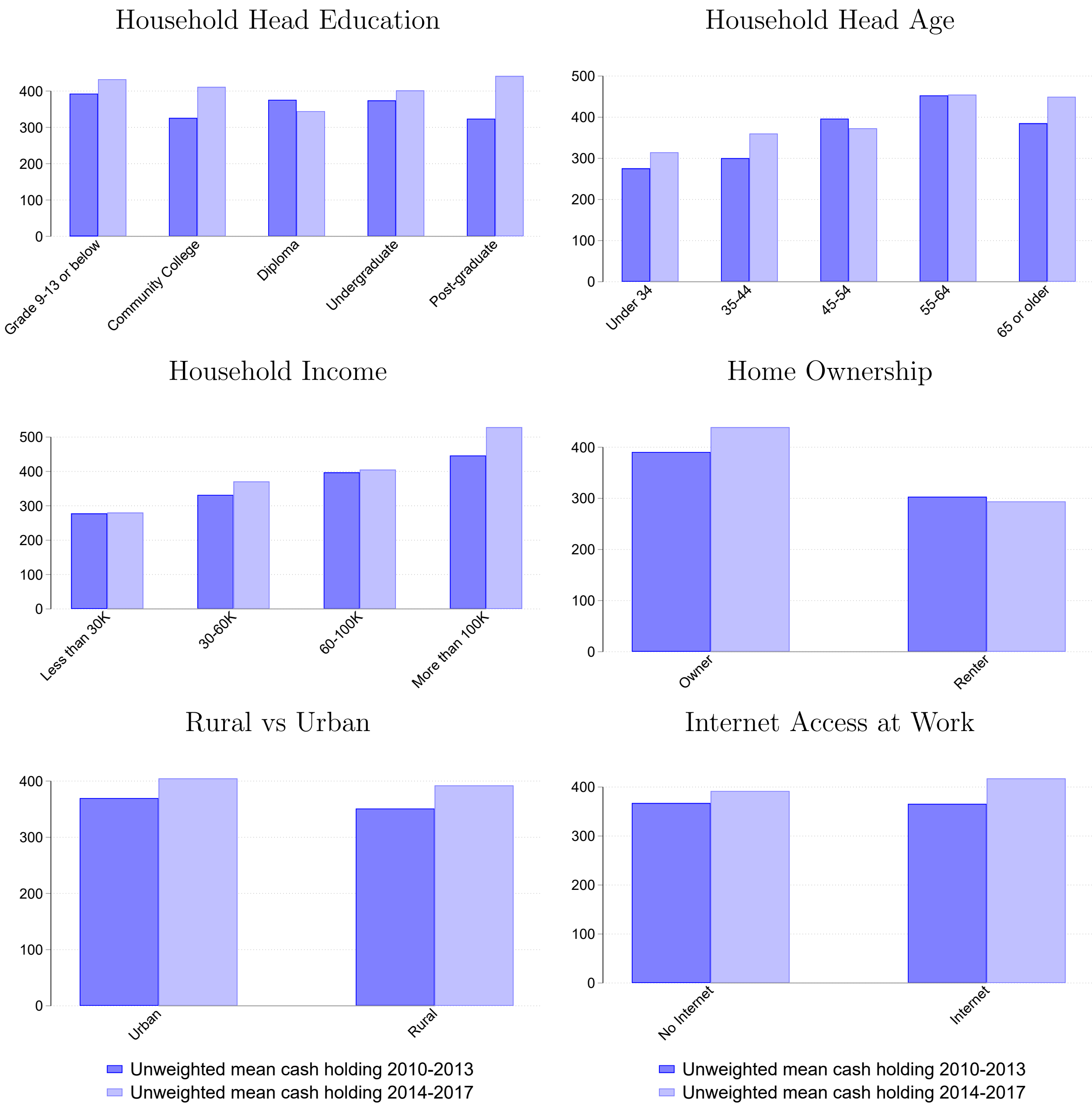
Figure E18: Deposit Holdings in Canadian Dollars across Demographic Groups



Data sources: CFM 2010–2017

Note: The bar charts show the unweighted mean deposit holdings across households and over the periods of 2010–2013 and 2014–2017 for different demographic groups in the merged sample of CFM and MOP data. The deposit holdings are deflated by CPI in each year.

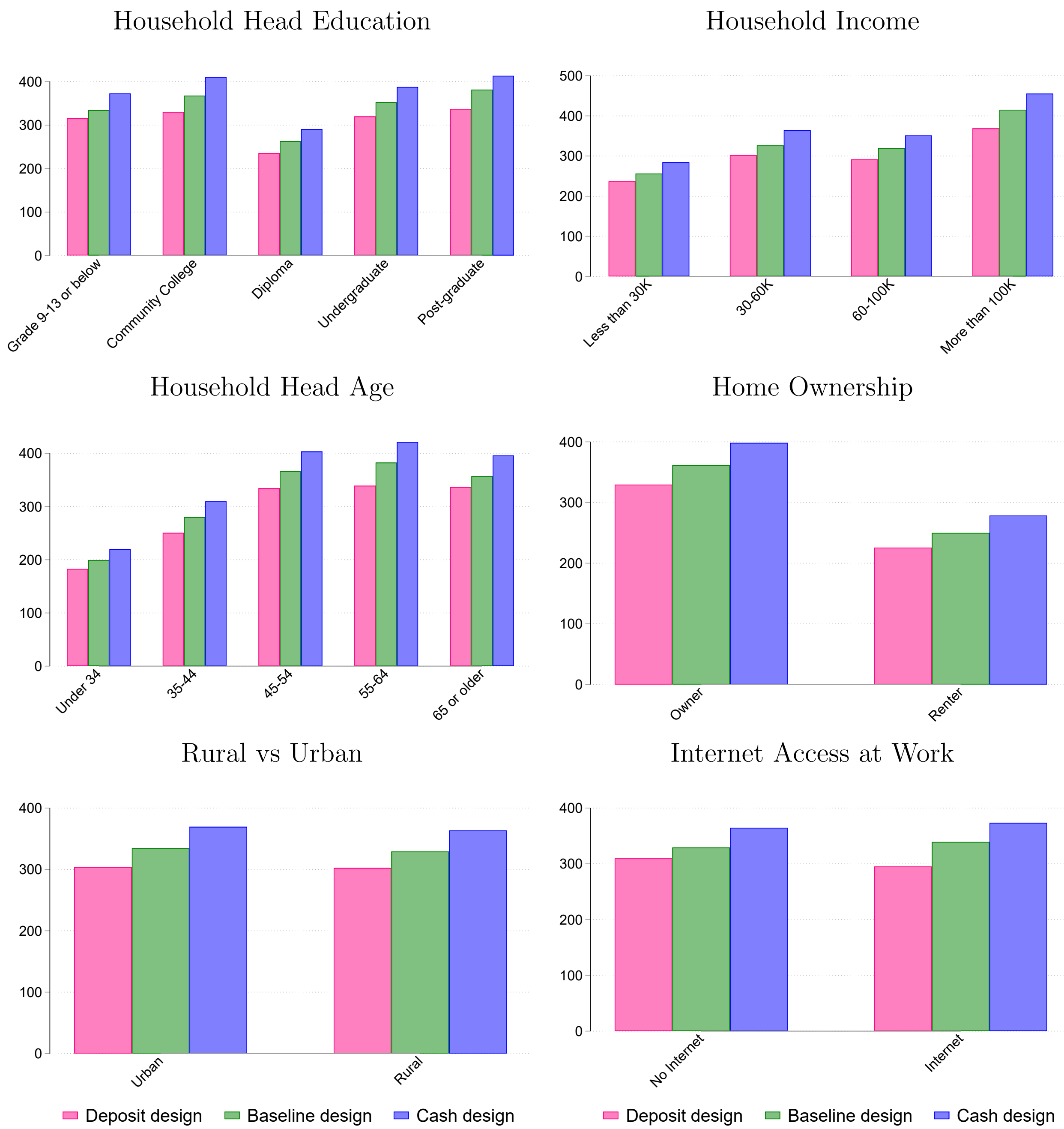
Figure E19: Cash Holdings in Canadian Dollars across Demographic Groups



Data sources: CFM 2010–2017

Note: The bar charts show the unweighted mean cash holdings across households and over the periods of 2010–2013 and 2014–2017 for different demographic groups in the merged sample of CFM and MOP data. The cash holdings are deflated by CPI in each year.

Figure E20: CBDC holdings in Canadian Dollars across Demographic Groups



Note: The bar charts show the unweighted mean predicted CBDC holdings across households and over the period of 2014–2017 for different demographic groups. For a given demographic group, the predicted CBDC holdings under three different designs are plotted. The CBDC holdings are predicted based on the logit model with the assumption that CBDC-specific effects are cash-like. The predicted CBDC holdings are deflated by CPI in each year.

E.7 Different Preference Parameters across Demographic Groups

In the baseline model, preference parameters are assumed to be identical across different demographic groups. In this section, I study whether the baseline results are robust if the preference parameters are allowed to differ across different demographic groups. Section E.7.1 studies how the preference parameters differ across demographic groups and Section E.7.2 shows the counterfactual results.

E.7.1 Estimation Results

In this section, I split the sample into two different subsamples based on one demographic variable each time, and estimate the demand parameters separately in each subsample. I focus on how the preference parameters will be different across the subsamples and only report these parameters here.

Table E13 and Table E14 show the estimated preference parameters in different subsamples. I split the sample based on six demographic variables: (1) household head age below or above (including) 45; (2) household head education below or above (including) undergraduate degree; (3) household income below or above (including) \$60K; (4) household living in urban or rural area; (5) household member has internet access at workplace/school; (6) household is a home owner or renter.

In each case, I test whether the preference parameters of a given attribute are statistically different across the two subsamples. Table E15 summarises the test results and shows the cases where the preference parameters are statistically different.

Table E15 shows that there are no statistically significant differences in the parameters for deposit rate, bundling of bank services, and the card unacceptance across the two subsamples based on a given demographic variable. The cost of use has a significantly larger impact on the deposit-to-cash ratio in the subsample of younger household heads (aged below 45) compared to that estimated in the subsample of older household heads, or in the sample of renters compared to home owners. The parameter for ease of use is significantly higher in the group of rural households. The parameter for security is significantly higher in the group of low-income households. Anonymity has a larger impact in the group of more highly educated households. Budgeting usefulness has a larger impact on asset allocation choices among rural households. Finally, the online transaction frequency matters more among the households with internet access at workplace/school.

Table E13: Preference Parameters Estimated Separately in Different Demographic Groups

	(1) Age $<$ 45	(2) Age $\geqslant$ 45	(3) $<$ Undergrad	(4) $\geqslant$ Undergrad	(5) Income $<$ 60K	(6) Income $\geqslant$ 60K
Deposit rate	4.538**	1.118	2.914**	0.809	2.082	2.997*
	(2.057)	(1.191)	(1.318)	(1.707)	(1.367)	(1.603)
Bank service	0.044	0.060***	0.069***	0.037	0.084***	0.038
	(0.033)	(0.021)	(0.022)	(0.033)	(0.025)	(0.026)
Cost of use	-0.913**	0.356	0.037	-0.011	-0.442	-0.000
	(0.373)	(0.248)	(0.272)	(0.312)	(0.296)	(0.282)
Ease/Convenience	1.296	0.415	0.691	-0.199	-0.296	0.737
	(1.015)	(0.542)	(0.734)	(0.643)	(0.681)	(0.657)
Security	0.426	0.376	0.421	0.440	0.920**	-0.231
	(0.451)	(0.318)	(0.357)	(0.388)	(0.368)	(0.367)
Anonymity	-0.064*	-0.032	0.001	-0.089***	-0.061**	-0.027
	(0.034)	(0.022)	(0.026)	(0.027)	(0.028)	(0.025)
Budgeting	-0.072**	-0.058***	-0.044*	-0.092***	-0.036	-0.064**
	(0.035)	(0.020)	(0.024)	(0.027)	(0.024)	(0.025)
Online payment	0.252	0.680*	0.504	0.264	1.019**	0.122
	(0.543)	(0.375)	(0.443)	(0.464)	(0.439)	(0.435)
Card unacceptance	-0.586	-0.164	-0.313	-0.056	-0.541**	-0.314
	(0.368)	(0.203)	(0.243)	(0.292)	(0.253)	(0.275)
Constant	0.785	1.768***	1.330***	2.740***	1.397***	3.286***
	(0.857)	(0.417)	(0.460)	(0.430)	(0.469)	(0.587)
Observations	1,419	2,933	2,590	1,762	2,054	2,298
Adjusted R^2	0.099	0.064	0.066	0.085	0.096	0.044

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Data sources: CFM 2010–2017, MOP 2013, CANNEX 2010–2017, Government of Canada website
The table shows the estimated preference parameters and the constant term using different demographic groups, i.e., household head aged below or above 45, household head education level below or above undergraduate degree, and household income below or above \$60K. The dependent variable is the log of deposit-to-cash ratio. Household characteristics included in each regression consist of household income, household head age, female head indicator, household head education, home ownership, household size, rural area indicator, internet access at work, attitudes towards stock market investment, feeling difficulty in paying off debt, the indicator of being behind debt obligations in the past year, and the bank, region, and year fixed effects.

Table E14: Preference Parameters Estimated Separately in Different Demographic Groups

	(1) Urban	(2) Rural	(3) No internet	(4) Internet	(5) Home owner	(6) Renter
Deposit rate	2.679**	-0.671	2.451*	2.185	3.429***	-0.131
	(1.150)	(2.555)	(1.287)	(1.756)	(1.211)	(2.043)
Bank service	0.059***	0.019	0.081***	0.024	0.054***	0.071**
	(0.020)	(0.044)	(0.022)	(0.030)	(0.021)	(0.035)
Cost of use	0.023	-0.677	-0.060	-0.130	0.133	-0.761*
	(0.217)	(0.579)	(0.276)	(0.308)	(0.231)	(0.438)
Ease/Convenience	-0.227	3.425**	0.572	0.290	0.552	-0.832
	(0.521)	(1.363)	(0.646)	(0.736)	(0.538)	(0.988)
Security	0.413	0.842	0.103	0.766**	0.523*	0.349
	(0.273)	(0.831)	(0.361)	(0.384)	(0.301)	(0.503)
Anonymity	-0.033*	-0.064	-0.069***	-0.009	-0.046**	-0.043
	(0.020)	(0.054)	(0.025)	(0.029)	(0.022)	(0.036)
Budgeting	-0.054***	-0.170***	-0.048**	-0.061**	-0.039*	-0.100***
	(0.019)	(0.057)	(0.023)	(0.029)	(0.020)	(0.036)
Online payment	0.329	0.594	-0.176	1.695***	0.366	0.933
	(0.377)	(0.583)	(0.383)	(0.520)	(0.339)	(0.939)
Card unacceptance	-0.282	-0.934	-0.264	-0.310	-0.318	-0.610
	(0.190)	(0.668)	(0.254)	(0.273)	(0.208)	(0.436)
Constant	1.315***	4.427***	1.677***	0.769	2.303***	0.215
	(0.436)	(0.985)	(0.464)	(0.901)	(0.475)	(0.641)
Observations	3,638	714	2,494	1,858	3,211	1,141
Adjusted R^2	0.077	0.077	0.071	0.073	0.042	0.118

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Data sources: CFM 2010–2017, MOP 2013, CANNEX 2010–2017, Government of Canada website

The table shows the estimated preference parameters using different demographic groups, i.e., urban or rural households, without or with access to internet at workplace/school, and home owner or renter. The dependent variable is the log of deposit-to-cash ratio. Household characteristics included in each regression consist of household income, household head age, female head indicator, household head education, home ownership, household size, rural area indicator, internet access at work, attitudes towards stock market investment, feeling difficulty in paying off debt, the indicator of being behind debt obligations in the past year, and the bank, region, and year fixed effects.

Table E15: Summary of Cases where Preference Parameters for a Given Attribute are Significantly Different across Demographic Groups

	Household Head Age		Education		Income		Location		Internet		Home	
	< 45	$\geqslant 45$	$<$ Uni	$\geqslant$ Uni	$<$ 60K	$\geqslant$ 60K	Urban	Rural	No	Yes	Owner	Renter
Deposit rate												
Bank service												
Cost of use	Higher	Lower									Lower	Higher
Ease/Convenience							Lower	Higher				
Security					Higher	Lower						
Anonymity			Lower	Higher								
Budgeting							Lower	Higher				
Online payment									Lower	Higher		
Card unacceptance												

Data sources: CFM 2010–2017, MOP 2013, CANNEX 2010–2017, Government of Canada website

Note: This table shows the cases where there is a significant difference between the preference parameters that are separately estimated using two different subsamples based on a given demographic variable. The column title shows different ways to split the sample. Each time, I split the sample into two subsamples, i.e., household heads aged below or above 45, education level below or above undergraduate degree, household income below or above \$60K, urban or rural households, with or without internet at workplace/school, and home owner or renter. The preference parameters are separately estimated in each of these subsamples and the results can be found in Table E13 and E14. "Higher" ("lower") indicates that the parameter is significantly higher (lower) than that in the other subsample. The null hypothesis that there is no difference in $\widehat{\alpha}_1$ from subsample 1 and $\widehat{\alpha}_2$ from subsample 2 is rejected if the test statistic $\frac{(\widehat{\alpha}_1-\widehat{\alpha}_1)^2}{\mathrm{Var}(\widehat{\alpha}_1)+\mathrm{Var}(\widehat{\alpha}_2)}$ is greater than the critical value of χ^2 distribution with one degree of freedom at a significance level of at least 10%.

E.7.2 Counterfactual Results

I find that although the parameters of some attributes can be significantly different across certain demographic groups, these differences are canceled out on an aggregate level and do not affect the aggregate-level predictions, as shown in Table E16 and Table E17.

Table E16 shows the predicted aggregate CBDC shares under a baseline design for CBDC based on a logit model, using the parameters that are estimated from different samples. The first row shows the baseline results where the whole sample is used to estimate the demand parameters, in which case the preference parameters are assumed to be identical across demographic groups. The other rows shows the results using two sets of different parameters to predict the aggregate CBDC shares. For example, in the second row, parameters are separately estimated in two subsamples depending on whether the household head's age is above or below (including) 45. To predict the aggregate CBDC share across households in the whole sample, the two sets of parameters are applied to the two subsamples conditional on the demographic group. As can be seen, the predictions for the aggregate CBDC shares are almost identical to the baseline results. Table E17 shows that the impacts of CBDC attribute changes using preference parameters separately estimated across demographic groups are also similar to the baseline results.

Table E16: Aggregate CBDC Shares Using Parameters Estimated in Different Samples

Sample(s) used to estimate parameters	Aggregate CBDC Share
Whole sample (Baseline)	4–52%
Age $<$ or $\geqslant$ 45	4–52%
Education $<$ or $\geqslant$ undergrad	4–52%
Household income $<$ or $\geqslant$ 60K	4–51%
Urban or rural area	4–53%
Internet at workplace or not	4–52%
Home owner or renter	4–51%

Note: The table shows the predicted aggregate share of a CBDC with a baseline design under the logit model, using the parameters that are estimated in different samples indicated by the first column. The first row shows the baseline results, where the whole sample is used to estimate the parameters and thus the preference parameters are the same across demographic groups. The other rows show the results using two sets of parameters that are separately estimated from two different subsamples divided based on a given demographic variable. For example, the second row shows the results after dividing the sample into the younger group (< 45) and the older group ($\geqslant$ 45). The range for the aggregate CBDC shares in the second column is due to different assumptions on the CBDC-specific effects.

Table E17: Impacts of CBDC Attributes Using Parameters Estimated in Different Samples

Sample(s) used to estimate parameters	% change in s_{cbdc} in response to change in a given CBDC attribute			
	Interest rate $0\% \rightarrow 0.1\%$	Budgeting usefulness $0.7 \rightarrow 0$	Anonymity $0.7 \rightarrow 0$	Bundling of bank service $0 \rightarrow 1$
Whole sample (Baseline)	10 to 23	-7 to 14	-5 to -10	4 to 8
Age $<$ or $\geqslant$ 45	8 to 18	-7 to -13	-5 to -9	4 to 8
Education $<$ or $\geqslant$ undergrad	9 to 21	-7 to -14	-5 to -9	4 to 8
Household income $<$ or $\geqslant$ 60K	13 to 28	-6 to -11	-6 to -11	4 to 8
Urban or rural area	10 to 24	-8 to -15	-5 to -10	3 to 7
Internet at workplace or not	11 to 25	-6 to -12	-5 to -11	4 to 9
Home owner or renter	14 to 31	-6 to -11	-6 to -12	4 to 8

Note: The table shows the percentage change in aggregate CBDC share when a given CBDC attribute changes relative to the baseline design, using the parameters that are estimated in different samples indicated by the first column. The column title shows the change in each CBDC attribute. The first row shows the baseline results, where the whole sample is used to estimate the parameters and thus the preference parameters are the same across demographic groups. The other rows show the results using two sets of parameters that are separately estimated from two different subsamples divided based on a given demographic variable. For example, the second row shows the results after dividing the sample into the younger group ($<$ 45) and the older group ($\geqslant$ 45). The range for the percentage change in aggregate CBDC shares in each cell is due to different assumptions on the CBDC-specific effects.

E.8 Endogenous Changes in Attributes of Existing Products

Section E.8.1 studies the potential change in the cost of using deposits to pay after CBDC issuance. Section E.8.2 studies the potential change in the merchant acceptance of deposits and cash after CBDC issuance.

E.8.1 Cost of Use for Deposits

Suppose after CBDC issuance, greater competition for electronic payments leads to lower interchange fees on cards for merchants. This would imply that merchants can pass the lower interchange fees onto consumers by charging consumers a lower service/convenience fee for certain types of transactions and hence consumers may find it cheaper to use cards. I find that the baseline results are robust to changing the cost of using deposits to pay after CBDC issuance.

More specifically, under the baseline analysis, debit card ratings are used to measure the cost of using deposits to pay. Assuming deposits become as cheap to use as cash after CBDC issuance, so that the cash ratings are used to measure the costs of deposit, Figure E21a shows that the aggregate CBDC share is almost unchanged relative to the baseline results. This is because (1) the estimated parameter for the cost of use is not large; (2) debit cards are not viewed as much more expensive to use than cash. In the 2013 MOP survey, 65% (88%) of people think debit card (cash) is a low-cost or very low-cost payment instrument.

E.8.2 Merchant Acceptance of Cards and Cash

Acceptance of cards and cash can potentially change after CBDC issuance. Since CBDC is likely to offer lower interchange fees, merchants may want to stop accepting cards and switch to CBDC. In addition, if cash usage continues declining going forward, accepting cash will become more costly for merchants due to the labor costs involved in handling cash.

In an extreme case where merchants no longer want to accept cards and cash but only accept CBDC, I find that the the aggregate CBDC share increases to 5–58%, as shown in Figure E21b. Note that the holdings of deposits and cash would not drop to zero in this case because they can still be used as store-of-value assets. The increase in CBDC share seems small, which is likely due to three reasons.

First, the parameter for the merchant acceptance feature is estimated in a sample where cash and cards are both widely accepted. Given data availability, I assume the acceptance rate of cash is one. The average acceptance rate of cards, measured by the fraction of transactions where cards are accepted in the 2013 MOP payment diary, is around 0.94 across all households in the estimation sample. By setting both the acceptance rates of cash and deposits to zero in the counterfactual analysis, I am extrapolating the relationship between the merchant acceptance feature and the deposit-to-cash ratio to a region that is far away from the estimation sample.

Second, the parameter estimated in the sample where cash and deposits both have high acceptance rates may understate the importance of merchant acceptance, compared to a situation where the acceptance rates for cash and deposits are very different. Since only the differences in attributes between deposits and cash would matter for the allocation between the two, if the acceptance rates of deposits and cash were identical, then the impact of the acceptance feature would not be identified.

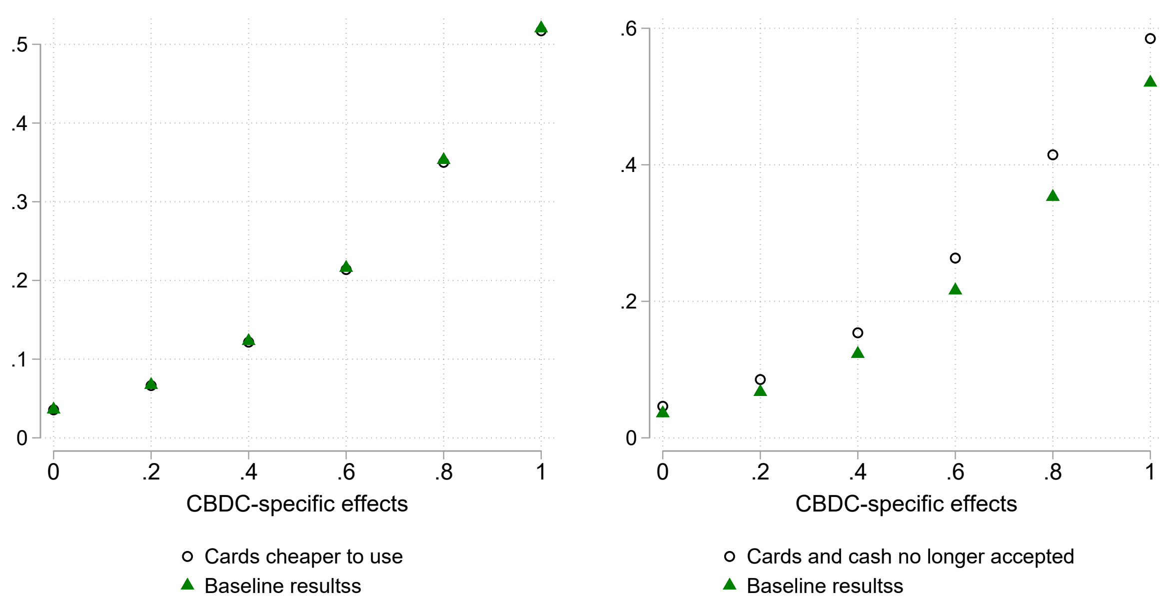
Third, other payment-related features for cash and deposits, such as the cost, ease, and security of using cash or deposits to make payments, are likely to change as well if merchant acceptance for cash and cards drops to zero. If other features of cash and deposits become worse as well, this can lead to a further increase in the demand for CBDC.

Modeling and estimating the merchants' problem will require information on how merchants make the acceptance decisions based on the costs of accepting a payment instrument (e.g., interchange fees on cards, labor costs involved in handling cash) and their customers' willingness to use a given payment instrument. This will be left for future research.

Figure E21: Aggregate CBDC Shares if Varying the Attributes of Deposits and Cash

(a) Aggregate CBDC Shares

(b) Aggregate CBDC Shares



Note: The figure shows the aggregate CBDC share under a baseline design and different assumptions for the CBDC-specific effects. The x-axis refers to the values of $\gamma_{cbdc}/\widehat{\gamma}_d$ and $\eta_{cbdc}/\widehat{\eta}_d$. At point of zero (one) on the x-axis, CBDC-specific effects are assumed to be cash-like (deposit-like), i.e., γ_{cbdc} and η_{cbdc} take the normalised values for cash (estimated values for deposits), so that $\gamma_{cbdc}/\widehat{\gamma}_d$ and $\eta_{cbdc}/\widehat{\eta}_d$ are both equal to zero (one). The left panel compares the baseline results with the case where cards are perceived to be as cheap to use as cash. The right panel compares the baseline results with the case where the acceptance rates of cards and cash are both set to zero.

F Incorporating Banks' Responses

Section F.1 solves the bank's problem. Section F.2 derives the interest rate elasticity of the aggregate deposit demand and shows why the introduction of CBDC can lead to a higher equilibrium deposit rate. Section F.3 discusses the counterfactual results on the impacts of changes in CBDC attributes after incorporating endogenous responses by banks.

F.1 Solving the Bank's Problem

Assume N identical banks compete for deposits *à la* Cournot. Each bank n chooses its deposit quantity D_n, taking all the other banks' quantities as given, to maximize the profit π_n:

$$\pi_n = \left[r^l - r^d(D_n + \sum_{k \neq n} D_k) - c \right] D_n \tag{F30}$$

where r^l is the exogenous return on loans, $r_d(.)$ is the deposit rate as a function of the total deposit quantity, and c is the marginal cost. Taking the first order condition with respect to D_j gives:

$$-\frac{\partial r^d}{\partial D_j} D_j + r^l - r^d - c = 0 \tag{F31}$$

Since the aggregate deposits are the sum of each bank's deposits $D = \sum_j D_j$, it can be seen that $\frac{\partial D}{\partial D_j} = 1$. This gives:

$$\frac{\partial r^d}{\partial D_j} = \frac{\partial r^d}{\partial D} \frac{\partial D}{\partial D_j} = \frac{\partial r^d}{\partial D} \tag{F32}$$

In equilibrium, $D_j = \frac{1}{N} D$. Using this equilibrium bank deposit quantity and (F32), (F31) can be written as:

$$r^l - r^d - c = \frac{\partial r^d}{\partial D} \frac{D}{N} \tag{F33}$$

where the left hand side is each bank's inverse semi-elasticity of deposit demand. Under the Cournot model with identical banks, each bank's semi-elasticity of deposit demand is simply the number of banks N multiplied by the semi-elasticity of the aggregate deposit demand $\frac{\partial D}{\partial r^d} \frac{1}{D}$.

F.2 Derivation of Aggregate Deposit Demand Elasticity

Before introducing CBDC, each household i's deposit share under the logit model is:

$$s_{i,d} = \frac{\exp(V_{i,d})}{\exp(V_{i,c}) + \exp(V_{i,d})} = \frac{1}{1 + \exp(V_{i,c} - V_{i,d})} \tag{F34}$$

Hence, the aggregate deposit demand D can be written as:

$$D = \sum_i s_{i,d} w_i = \sum_i \frac{w_i}{1 + \exp(V_{i,c} - V_{i,d})} \tag{F35}$$

Note that the observed utility from deposits $V_{i,d}$ contains how people value the post-tax rate of return on deposits, $\alpha r^d(1 - T_i)$, where T_i is the marginal tax rate on household income. In the estimation, household-specific deposit rates r_i^d (i.e., due to households banking with different main financial institutions) are used, but in the counterfactual analysis, I use the average deposit rate r^d across households to be consistent with the Cournot model that there is one equilibrium deposit rate. Differentiate the aggregate deposit demand with respect to the deposit rate r^d:

$$\begin{aligned}
\frac{\partial D}{\partial r^d} &= \sum_i -\frac{w_i}{[1 + \exp(V_{i,c} - V_{i,d})]^2} \exp(V_{i,c} - V_{i,d})(-\alpha)(1 - T_i) \\
&= \alpha \sum_i s_{i,d}^2 w_i \exp(V_{i,c} - V_{i,d})(1 - T_i) \\
&= \alpha \sum_i s_{i,d}^2 w_i \frac{s_{i,c}}{s_{i,d}}(1 - T_i) \\
&= \alpha \sum_i s_{i,d} w_i (1 - s_{i,d})(1 - T_i)
\end{aligned} \tag{F36}$$

where the last step uses $s_{i,c} = 1 - s_{i,d}$. Hence, the semi-elasticity of aggregate deposit demand can be written as:

$$\frac{\partial D}{\partial r^d}\frac{1}{D} = \alpha \sum_i \frac{s_{i,d} w_i}{D}(1 - s_{i,d})(1 - T_i) \tag{F37}$$

Note that $\frac{s_{i,d} w_i}{D}$ is each household's deposit holding as a percentage of the aggregate deposits, which acts like a weight. When CBDC is introduced under the logit model, $s_{i,d}$ would be reduced to:

$$s_{i,d} = \frac{\exp(V_{i,d})}{\exp(V_{i,d}) + \exp(V_{i,c}) + \exp(V_{i,cbdc})} \tag{F38}$$

Comparing with (F34), the extra term $\exp(V_{i,cbdc})$ in the denominator lowers $s_{i,d}$. Therefore, the presence of CBDC tends to make the aggregate deposit demand more elastic, as shown in (F37). Assuming the number of banks N is unchanged, this implies that each bank faces a more elastic deposit demand, since bank's semi-elasticity of deposit demand is $\frac{\partial D}{\partial r^d}\frac{N}{D}$. Given r^l and c are assumed to be exogenous and unchanged, (F33) implies that the equilibrium deposit rate tends to be higher when bank deposit demand is more elastic.

F.3 Counterfactual Results

Table F18 shows the percentage change in aggregate CBDC shares s_{cbdc} in response to a change in CBDC attribute relative to the baseline CBDC design under a logit model. The second column describes how a given CBDC attribute changes relative to the baseline design. The last four columns show the percentage changes in s_{cbdc} under different number of banks N. Note that only $N = 11$ is calibrated to match the weighted average net interest income over total assets ratio of around 1.5% in 2017. With $N = 6$ ($N = 20$), the implied bank profit margin is around 3.0% (0.9%). With $N = \infty$, the bank profit margin is zero and banks do not have market power to respond to CBDC, in which case the results are identical to the baseline results based on the households' demand side only.

As can be seen, when N is smaller and banks have more market power, the percentage changes in s_{cbdc} tend to be smaller and the range of predictions in each cell due to different assumptions on the CBDC-specific effects is narrowed.

Table F18: Impacts of Changes in CBDC Attributes under Different Number of Banks

Design attribute	Change in attribute relative to baseline design	% change in s_{cbdc} N = 6	N = 11	N = 20	N = ∞
Interest rate	0% $\to$ 0.1%	9 to 14	13 to 16	15 to 18	10 to 23
Budgeting usefulness	0.7 $\to$ 0	-5 to -9	-8 to -10	-9 to -11	-7 to -14
Anonymity	0.7 $\to$ 0	-4 to -7	-6 to -8	-7 to -8	-5 to -10
Bundling of bank service	0 $\to$ 1	3 to 5	5 to 6	5 to 7	4 to 8

Note: The table shows the percentage change in aggregate CBDC share s_{cbdc} in response to a change in CBDC attribute based on the logit model. The second column describes the change in CBDC attribute relative to the baseline design. The first number in each cell of the second column shows the value of the given CBDC attribute under the baseline design and the second number indicates the new value after the change. The last four columns show the predicted percentage changes in s_{cbdc} in response to the attribute change, using different calibration for the number of banks N. Note that only $N = 11$ is calibrated to match the weighted average net interest income over total assets ratio across banks. When N is infinity, the results are identical to the baseline results shown in the paper. The range of predictions in each cell of the last four columns are due to different assumptions on the CBDC-specific effects.

G Incorporating Network Effects

Section G.1 extends the baseline model to incorporate network effects. Section G.2 uses the extended model to estimate the parameters. Section G.3 compares the counterfactual results in the presence of network effects with the baseline results.

G.1 Extending Baseline Model

To incorporate network effects into the model, I follow the theoretical literature on modeling social interactions in a discrete choice framework (e.g., Blume et al., 2011; Brock and Durlauf, 2002, 2001). The novelty of this literature lies in (1) introducing interdependencies between the individual payoff and the others' actions and (2) imposing self-consistency between individual beliefs about the others' actions and conditional expectations of the others' actions (Brock and Durlauf, 2002).

Assume households belong to different groups and they interact with each other within their group g or network. Let $\mu_i^e(a_{-i,j})$ denote household i's belief about the actions $a_{-i,j}$ of the others in i's group $g(i)$. Household i's utility obtained from product j, where $j \in \{c, d\}$, is now written as:

$$u_{i,j} = V_{i,j} + \beta\mu_i^e(a_{-i,j}) + \epsilon_{i,j} \qquad \forall i \in g(i) \tag{G39}$$

where $V_{i,j} \equiv \boldsymbol{\alpha}'\boldsymbol{x}_{i,j} + \boldsymbol{\gamma}_j'\boldsymbol{z}_i + \eta_j$ is the "deterministic private utility" shown in the baseline model and $\beta\mu_i^e(a_{-i,j})$ captures the "deterministic social utility" (Blume et al., 2011). The new term, $\mu_i^e(a_{-i,j})$, introduces interdependencies between a given household's utility and the others' actions. The parameter β reflects the network effects. When β is positive, this implies that each household's choice would be positively influenced by the the others. When $\beta = 0$, this is reduced to the baseline model without network effects.

Assuming beliefs are independent from the random utility shock $\epsilon_{i,j}$ and $\epsilon_{i,j}$ comes from a distribution that is i.i.d. Type I extreme value, the household i's probability of choosing $j \in \{c, d\}$ is:

$$P_{i,j} = \frac{\exp(V_{i,j} + \beta\mu_i^e(a_{-i,j}))}{\exp(V_{i,d} + \beta\mu_i^e(a_{-i,d})) + \exp(V_{i,c} + \beta\mu_i^e(a_{-i,c}))} \tag{G40}$$

Since the discrete choice between cash and deposits is made for each dollar of i's endowment of liquid assets, the choice probability $P_{i,j}$ is equivalent to the asset j's share $s_{i,j}$ out of the liquid assets by the law of large numbers.

Using (G40) and modeling the others' actions $a_{-i,j}$ as logged asset share $s_{-i,j}$, the log of deposit-to-cash ratio can be written as:

$$\ln \frac{s_{i,d}}{s_{i,c}} = V_{i,d} - V_{i,c} + \beta(\mu_i^e(\ln s_{-i,d}) - \mu_i^e(\ln s_{-i,c})) \tag{G41}$$

where the share of asset j, $s_{i,j} \equiv \frac{q_{i,j}}{w_i}$, is the holding of asset j out of the liquid asset endowment w_i. One deviation from the literature on modeling social interactions in discrete choice models is that here, $a_{i,j}$ is an asset share instead of a discrete choice between 0 or 1. This is because the asset shares are observed in the data. With assumptions on μ_i^e discussed below, it can be shown that the model can be reduced to a linear-in-means specification which is often used in the empirical studies of network effects (e.g., Aizer and Currie, 2004; Gowrisankaran and Stavins, 2004; Bertrand, Luttmer and Mullainathan, 2000).

The standard assumption used to close the model is to impose an equilibrium condition which ensures self-consistency between subjective beliefs μ_i^e and objective conditional expectations μ given i's information set F_i:

$$\mu_i^e(\ln s_{-i,j}) = \mu(\ln s_{-i,j}|F_i) \tag{G42}$$

where F_i consists of $(\boldsymbol{x}_{k,j})_{k\in g(i)}$, $(\boldsymbol{z}_k)_{k\in g(i)}$, and η_j, which are observed by all individuals in group $g(i)$. Although individuals also observe their own random private utility shock $\epsilon_{i,j}$, they do not internalize the effect of their choice (given the realized $\epsilon_{i,j}$) on the others' choices once assuming that individuals are small relative to the group. The conditional expectation of others' logged asset shares can be modeled as:

$$\mu(\ln s_{-i,j}|F_i) = \sum_{k\in g(i),k\neq i} \theta_{i,k} E(\ln s_{k,j}|F_i) \tag{G43}$$

where $\theta_{i,k}$ measures the connection between i and k in household i's network. In empirical studies of social interactions, it is often assumed that $\theta_{i,k} = \frac{1}{n_g-1}$ for all $k \in g(i)$ and $k \neq i$, where n_g is the number of people in the group g. Using $\theta_{i,k} = \frac{1}{n_g-1}$, together with (G42) and (G43), (G41) can be written as:

$$\ln \frac{s_{i,d}}{s_{i,c}} = V_{i,d} - V_{i,c} + \beta E\left(\overline{\ln \frac{s_{k,d}}{s_{k,c}}}\middle| F_i\right) \tag{G44}$$

where $\overline{\ln \frac{s_{k,d}}{s_{k,c}}} \equiv \frac{1}{n_g-1}\sum_{k\in g(i),k\neq i} \ln \frac{s_{k,d}}{s_{k,c}}$ is the average of logged deposit-to-cash ratios across all households k in group $g(i)$ except for i. In empirical implementation discussed below, I assume household i observes the mean behavior across households within group $g(i)$, so the expectation term is replaced by the group mean calculated from the data, where the group mean excludes i's value.

G.2 Estimating the Network Effects

Section G.2.1 explains why it is in general difficult to empirically identify the presence of the network effects. Section G.2.2 shows how the network is defined and measured empirically. Section G.2.3 explains how I partly address the identification challenge discussed in Section G.2.1. Lastly, Section G.2.4 shows the estimation results where the estimated parameters are used to conduct counterfactual analyses in Section G.3.

G.2.1 Identification Challenge

I use the linear-in-means model (G44) to estimate the demand parameters, following the empirical literature on estimating the network effects (e.g., Gowrisankaran and Stavins, 2004; Bertrand, Luttmer and Mullainathan, 2000). Identifying the network effects β is difficult due to the reflection problem (Manski, 1993). Manski (1993) outlined three competing hypotheses in explaining the correlation between the individual's choice and the choices of the others in the same group. That is, the observed correlation could be because (1) the individual is influenced by the others in the same group (endogenous effects); (2) individuals in the same group share similar characteristics (contextual effects); or (3) individuals in the same group face common shocks (correlated effects). In the context of this paper, the endogenous effects refer to the network effects. Due to the presence of contextual and correlated effects, it is difficult to distinguish the network effects from the other hypotheses.

As noted in Bertrand, Luttmer and Mullainathan (2000), the reflection problem can be viewed as a manifestation of two omitted variable biases, i.e., omitted personal characteristics and omitted group characteristics may be correlated with the group behavior. In my case, one example of the omitted personal characteristics could be that individuals from some groups may have less trust in commercial banks and prefer to hold more cash. An example of omitted group characteristics could be a certain group may have better access to the ATMs, which tends to affect the preferences for cash holdings for all individuals within the group. These omitted variables show that the households' allocation decisions can be related to the others' decisions because households within the same group tend to share similar characteristics and face common shocks, and not because households are influenced by the others via interactions. These omitted variables are likely to cause an upward bias in β. I discuss how I deal with the reflection problem after defining the network below.

G.2.2 Network Definition

I divide households into different groups/networks based on their geographical locations indicated by the six-digit postcodes. Table G19 shows the definition of the network ranging from the first 3 digits of postcode (FSA level) to circular area around a given household with the radius being the great-circle distance to the household. Since the merged sample between CFM and MOP data that is used for estimation is too small, I find the neighbors of each household in the merged sample using the whole CFM sample with around 12,000 households each year. Table G19 shows the summary statistics of the number of neighbors by households from the urban/rural area based on different group definitions. For instance, within 10km from an urban household's location, the median number of nearby neighbors across all households in the merged sample is 73.

Table G19: Number of Nearby Neighbors Based on Different Network Definition

	Urban				Rural			
	Min	Median	Max	Mean	Min	Median	Max	Mean
first 3 digits of postcode	2	8	28	8	2	16	56	16
first 2 digits of postcode	4	84	211	87	14	131	229	140
urban 10km/rural 30km	2	73	410	91	2	19	551	40
urban 10km/rural 50km	2	73	410	91	2	50	897	100
urban 20km/rural 70km	2	179	754	210	2	115	1569	199

Data sources: CFM whole sample 2010–2017, CFM and MOP merged sample 2010–2017
Note: The table shows the summary statistics of the number of nearby neighbors around each urban/rural household in the merged sample using different network definitions based on households' geographical locations by six-digit postcodes. The neighbors are found using the whole CFM sample that contains about 12,000 households per year. The summary statistics are calculated for households in the merged sample.

G.2.3 Empirical Implementation

To partly deal with the omitted group characteristics, I control for the regional dummies and the dummy of rural area, so common shocks occurring at the regional level can be absorbed by the dummies. Having the data on household locations by six-digit postcodes allows me to define the network on a more granular level, so that the regional dummies do not take away all the variation in the group mean. For example, if household location was only known at the province level, then the group mean calculated by province and year would largely be absorbed by the regional dummies. However, it is hard to rule out the correlation between unobserved personal characteristics and the group mean. As in Bertrand, Luttmer and

Mullainathan (2000), $\widehat{\beta}$ may therefore capture both the network effects and the contextual effects and thus network effects could be overstated from the estimate $\widehat{\beta}$.

G.2.4 Estimated Demand Parameters

Table G20 shows the estimated preference parameters and the network effects $\widehat{\beta}$ using three different network definitions. The network definition is selected based on the criteria that the network size cannot be too small, in which case the number n_g of neighbors is too small to calculate the group mean precisely. On the other hand, if the network size is too big, then there is less variation in the group mean across different groups.

In each column of Table G20, the only difference from the baseline model is the inclusion of a group mean, i.e., the mean of logged deposit-to-cash ratios across all households $k \neq i$ belonging to group $g(i)$. As shown in Table G20, $\widehat{\beta}$ is positive in all cases. However, $\widehat{\beta}$ is only significant in some specifications, which is likely due to two reasons. First, there needs to be enough variation in the group mean across groups. When the group is defined based on the first two digits of households' postcodes, the regional dummies alone explain around 20% of the variation in the group mean. This explains why $\widehat{\beta}$ is not significant in columns (1)-(3). By contrast, when overlapping networks (i.e., defined based on great-circle distances) are used as in columns (4)-(9), the regional dummies only explain around 5% of the variation in the group mean.

Second, including households with too few nearby neighbors can cause noise in the group, which may explain why $\widehat{\beta}$ is close to zero in column (4) and (7). When only keeping those households with more than 10 neighbors, i.e., $n_g > 10$, $\widehat{\beta}$ increases, as shown in columns (5) and (8). When $n_g > 30$, $\widehat{\beta}$ increases further and becomes significant, as shown in columns (6) and (9).

As discussed in G.2.3, since $\widehat{\beta}$ may capture both the network effects and the contextual effects, a positive $\widehat{\beta}$ does not necessarily mean network effects exist. The significantly positive $\widehat{\beta}$ found in some cases suggests that the network effects are potentially present. In the counterfactual analysis below, I assume $\widehat{\beta}$ does capture some network effects, and use the specification and sample shown in the last column of Table G20 to conduct counterfactual analyses in the section below.

G.3 Counterfactual Results

In this section, I first show how I solve for the expected group means of asset shares once CBDC is introduced in Section G.3.1 and then explain the mechanism for network effects in Section G.3.2. Finally, I discuss the counterfactual results in Section G.3.3.

Table G20: Estimating Network Effects Using Different Network Definitions and Samples

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$n_g > 0$	$n_g > 10$	$n_g > 30$	$n_g > 0$	$n_g > 10$	$n_g > 30$	$n_g > 0$	$n_g > 10$	$n_g > 30$
Mean by first 2 digits of postcode excl i	0.101	0.113	0.044						
	(0.116)	(0.117)	(0.130)						
Mean by urban 10km/rural 30km excl i				0.052	0.143	0.391**			
				(0.050)	(0.102)	(0.165)			
Mean by urban 10km/rural 50km excl i							0.043	0.077	0.273*
							(0.057)	(0.106)	(0.165)
Deposit rate	2.217**	2.247**	1.827*	2.276**	1.877	2.248*	2.254**	1.867	1.797
	(1.035)	(1.037)	(1.045)	(1.042)	(1.162)	(1.358)	(1.039)	(1.137)	(1.292)
Bank service	0.059***	0.059***	0.056***	0.057***	0.045**	0.037	0.059***	0.047**	0.048**
	(0.018)	(0.018)	(0.018)	(0.018)	(0.020)	(0.024)	(0.018)	(0.020)	(0.023)
Cost of use	-0.110	-0.088	-0.177	-0.119	-0.305	-0.302	-0.114	-0.205	-0.189
	(0.202)	(0.202)	(0.205)	(0.203)	(0.220)	(0.250)	(0.203)	(0.216)	(0.239)
Ease/Convenience	0.380	0.417	0.294	0.337	0.127	-0.505	0.359	0.317	-0.213
	(0.466)	(0.467)	(0.476)	(0.469)	(0.519)	(0.570)	(0.467)	(0.508)	(0.557)
Security	0.448*	0.467*	0.607**	0.516**	0.704**	1.019***	0.519**	0.758***	0.962***
	(0.257)	(0.256)	(0.264)	(0.259)	(0.284)	(0.319)	(0.257)	(0.278)	(0.307)
Anonymity	-0.037**	-0.038**	-0.045**	-0.036*	-0.033	-0.039*	-0.037**	-0.035*	-0.045**
	(0.018)	(0.018)	(0.019)	(0.019)	(0.020)	(0.023)	(0.018)	(0.020)	(0.022)
Budgeting	-0.062***	-0.059***	-0.057***	-0.068***	-0.071***	-0.076***	-0.067***	-0.068***	-0.082***
	(0.017)	(0.018)	(0.018)	(0.018)	(0.020)	(0.022)	(0.018)	(0.019)	(0.021)
Online payment	0.444	0.461	0.439	0.456	0.663*	0.556	0.457	0.686**	0.603
	(0.314)	(0.314)	(0.318)	(0.317)	(0.354)	(0.413)	(0.316)	(0.349)	(0.402)
Card unacceptance	-0.287	-0.285	-0.316*	-0.244	-0.179	-0.461**	-0.235	-0.185	-0.342
	(0.181)	(0.181)	(0.183)	(0.182)	(0.196)	(0.218)	(0.182)	(0.193)	(0.212)
Constant	1.432***	1.360***	1.477***	1.556***	1.450***	0.541	1.591***	1.604***	0.858
	(0.485)	(0.488)	(0.519)	(0.421)	(0.523)	(0.691)	(0.429)	(0.521)	(0.677)
Observations	4,352	4,337	4,142	4,273	3,599	2,812	4,302	3,727	2,990
Adjusted R^2	0.070	0.069	0.071	0.071	0.068	0.075	0.071	0.067	0.073

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Data sources: CFM 2010–2017, MOP 2013, CANNEX 2010–2017, Government of Canada website

Note: The table shows the estimated parameter for the group mean (capturing network effects), preference parameters for the product attributes, and the constant term from regressing the log of deposit-to-cash ratio on the group mean, product attributes, and household characteristics (i.e., household income, household head age, female head indicator, household head education, home ownership, household size, rural area indicator, internet access at work, attitudes towards stock market investment, feeling difficulty in paying off debt, the indicator of being behind debt obligations in the past year, and the bank, region, and year fixed effects). The first three rows show the group means calculated using different network definitions and estimation samples. “Mean by first digits of postcode excl i” refers to the group mean of logged deposit-to-cash ratios across households other than i within a two-digit postcode area. Similarly, “Mean by urban 10km/rural 30km excl i” refers to the group mean of logged deposit-to-cash ratios across households other than i within 10km from an urban household i or within 30km from a rural household i. Each column title indicates the different estimation samples used based on the number of nearby neighbors n_g around a given household. For example, $n_g > 30$ means that only households with more than 30 nearby neighbors are kept in the sample.

G.3.1 Solving for Expected Group Means of Asset Shares

When introducing CBDC in the counterfactual analysis, I assume the same β that captures network effects applies to all three products, i.e., cash, deposits, and CBDC. Based on (G44), it can be shown that for each household i in group $g(i)$, the logged asset share ratios are as follows:

$$\ln\frac{s_{i,d}}{s_{i,c}} = V_{i,d} - V_{i,c} + \beta(E[\overline{\ln s_{k,d}}] - E[\overline{\ln s_{k,c}}]) \tag{G45}$$

$$\ln\frac{s_{i,d}}{s_{i,cbdc}} = V_{i,d} - V_{i,cbdc} + \beta(E[\overline{\ln s_{k,d}}] - E[\overline{\ln s_{k,cbdc}}]) \tag{G46}$$

$$\ln\frac{s_{i,c}}{s_{i,cbdc}} = V_{i,c} - V_{i,cbdc} + \beta(E[\overline{\ln s_{k,c}}] - E[\overline{\ln s_{k,cbdc}}]) \tag{G47}$$

where $E[\overline{\ln s_{k,j}}]$ refers to the expected group mean of logged asset j shares across all households k in group $g(i)$ and $\overline{\ln s_{k,j}} = \frac{1}{n_g}\sum_{k\in g(i)} \ln s_{k,j}$ denotes the group mean. The private utilities $V_{i,j}$ for $j \in \{c, d, cbdc\}$ can be calculated from the estimated parameters and the data. Note that the difference in the expected group mean of the logged asset shares can be written as the expected group mean of the logged assets ratio:

$$\begin{aligned}
E[\overline{\ln s_{k,d}}] - E[\overline{\ln s_{k,c}}] &= E[\overline{\ln s_{k,d}} - \overline{\ln s_{k,c}}] \\
&= E\left[\frac{1}{n_g}\sum_{k\in g(i)} \ln s_{k,d} - \frac{1}{n_g}\sum_{k\in g(i)} \ln s_{k,c}\right] \\
&= E\left[\frac{1}{n_g}\sum_{k\in g(i)} (\ln s_{k,d} - \ln s_{k,c})\right] \\
&= E\left[\frac{1}{n_g}\sum_{k\in g(i)} \ln\frac{s_{k,d}}{s_{k,c}}\right] = E\left[\overline{\ln\frac{s_{k,d}}{s_{k,c}}}\right]
\end{aligned} \tag{G48}$$

Therefore, writing (G45), (G46), and (G47) in terms of the difference in the expected group mean of logged asset shares is the same as in (G44) where the expected group mean of logged assets ratio.

I solve for the expected group mean of logged asset shares $E[\overline{\ln s_{i,cbdc}}]$, $E[\overline{\ln s_{i,d}}]$, and $E[\overline{\ln s_{i,c}}]$ using fixed point iteration. Given the data limitation on the estimation sample size, which is too small to divide people into different groups based on the same definitions used in empirical estimation, I assume a global network where all households in the estimation sample belong to the same network in the counterfactual analysis. Starting with a set of initial values for the three expected mean asset shares, the predicted assets shares for each household can be calculated and then averaged, which are then used to update the initial values of the expected mean asset shares. Iterating this process and upon convergence, the average of the predicted asset shares across households equals the expected mean asset share $E[\overline{\ln s_{i,j}}]$ for $j \in \{c, d, cbdc\}$.

G.3.2 The Role of Network Effects

To see how β changes the allocation of asset shares, take an expectation of both sides in (G45), (G46), (G47), and then average across households and rearrange to get:

$$E\left[\overline{\ln\frac{s_{i,d}}{s_{i,c}}}\right] = \frac{1}{1-\beta}(\overline{V_{i,d} - V_{i,c}}) \tag{G49}$$

$$E\left[\overline{\ln\frac{s_{i,d}}{s_{i,cbdc}}}\right] = \frac{1}{1-\beta}(\overline{V_{i,d} - V_{i,cbdc}}) \tag{G50}$$

$$E\left[\overline{\ln\frac{s_{i,c}}{s_{i,cbdc}}}\right] = \frac{1}{1-\beta}(\overline{V_{i,c} - V_{i,cbdc}}) \tag{G51}$$

where $\overline{V_{i,d} - V_{i,c}}$ denotes the average utility difference between deposits and cash across households. As can be seen, the main effect of β is to amplify the utility differences among products by a factor of $\frac{1}{1-\beta}$ provided that $\beta \in (0, 1)$. If the private utilities $V_{i,j}$ were equal across products, then the network effects would not have any impact on the allocation of asset shares. Since the private utility differences on the right hand side of (G49), (G50), (G51) are deterministic and are known by households, the expectation sign can be removed:

$$\overline{\ln\frac{s_{i,d}}{s_{i,c}}} = \frac{1}{1-\beta}(\overline{V_{i,d} - V_{i,c}}) \tag{G52}$$

$$\overline{\ln\frac{s_{i,d}}{s_{i,cbdc}}} = \frac{1}{1-\beta}(\overline{V_{i,d} - V_{i,cbdc}}) \tag{G53}$$

$$\overline{\ln\frac{s_{i,c}}{s_{i,cbdc}}} = \frac{1}{1-\beta}(\overline{V_{i,c} - V_{i,cbdc}}) \tag{G54}$$

To see how the CBDC share $s_{i,cbdc}$ changes with β, it is useful to write the CBDC share in terms of the asset ratios. Since the asset shares sum to one for each household:

$$s_{i,cbdc} + s_{i,d} + s_{i,c} = 1 \tag{G55}$$

it follows that:

$$s_{i,cbdc} = \frac{1}{1 + \frac{s_{i,d}}{s_{i,cbdc}} + \frac{s_{i,c}}{s_{i,cbdc}}} \tag{G56}$$

after dividing both sides of (G55) by $s_{i,cbdc}$ and rearranging. In the baseline logit model without the network effects, the asset ratios can be written in terms of the private utility difference, i.e., $\frac{s_{i,d}}{s_{i,cbdc}} = \exp(V_{i,d} - V_{i,cbdc})$ and $\frac{s_{i,c}}{s_{i,cbdc}} = \exp(V_{i,c} - V_{i,cbdc})$. As a result, the CBDC share (G56) has a closed-form expression:

$$s_{i,cbdc} = \frac{1}{1 + \exp(V_{i,d} - V_{i,cbdc}) + \exp(V_{i,c} - V_{i,cbdc})} \tag{G57}$$

In contrast, when the network effects are present, there is no closed-form expression for $s_{i,cbdc}$. As shown in (G52), (G53), and (G54), the group mean of the logged asset ratios depends on the amplified group mean of the private utility differences in the presence of network effects. Due to the averaging involved, the asset ratios cannot be written as the exponentials of the private utility differences and β.

However, in a special case when all households in the same group $g(i)$ are assumed to have the same private utilities, i.e., $V_{i,j} = V_j$, then (G53) and (G54) can be written as:

$$\ln \frac{s_d}{s_{cbdc}} = \frac{1}{1-\beta}(V_d - V_{cbdc}) \tag{G58}$$

$$\ln \frac{s_c}{s_{cbdc}} = \frac{1}{1-\beta}(V_c - V_{cbdc}) \tag{G59}$$

Taking exponentials of both sides of (G58) and (G59) and substituting into (G56) to get:

$$s_{cbdc} = \frac{1}{1 + \exp\left(\frac{1}{1-\beta}(V_d - V_{cbdc})\right) + \exp\left(\frac{1}{1-\beta}(V_c - V_{cbdc})\right)} \tag{G60}$$

which is equivalent to the aggregate CBDC share, assuming that all households belong to the same group/network. As can be seen from (G60), s_{cbdc} depends on the private utility V_{cbdc} from CBDC relative to those for deposits and cash, as in the case without the network effects (G57). The only difference here is that the private utility differences are amplified by a factor of $\frac{1}{1-\beta}$ provided that $\beta \in (0, 1)$.

I focus on the utility difference between deposits and CBDC in discussing the role of β below, since Table G21 shows that the exponential term, $\exp\left(\frac{1}{1-\beta}(V_c - V_{cbdc})\right)$, stays close to zero most of the time, suggesting that the utility difference between cash and CBDC is not a driving factor for s_{cbdc}. Intuitively, cash gives a lower private utility than deposits, so how CBDC compares with cash is less important than how it compares with deposits.

In the presence of strong network effects, even if V_{cbdc} is only slightly higher (lower) than V_d, this small private utility difference $(V_d - V_{cbdc})$ can be amplified by a lot. The exponential of this amplified negative (positive) utility difference then approaches zero (a large positive number), which tends to push s_{cbdc} towards one (zero). This can be seen from Table G21 by

Table G21: Decomposing the Aggregate CBDC Share in the Special Case

	CBDC-specific effects					
	0	0.2	0.4	0.6	0.8	1
Private utility differences						
$V_d - V_{cbdc}$	2.39	1.86	1.33	0.80	0.27	-0.26
$V_c - V_{cbdc}$	0.12	-0.41	-0.94	-1.46	-1.99	-2.52
Without network effects ($\beta = 0$)						
$\exp(V_d - V_{cbdc})$	10.86	6.40	3.77	2.22	1.31	0.77
$\exp(V_c - V_{cbdc})$	1.13	0.67	0.39	0.23	0.14	0.08
$s_{cbdc} = \frac{1}{1+\exp(V_d - V_{cbdc})+\exp(V_c - V_{cbdc})}$	0.08	0.12	0.19	0.29	0.41	0.54
With strong network effects ($\beta = 0.9$)						
$\exp(10 * (V_d - V_{cbdc}))$	2.29e+10	1.15e+08	575195.63	2881.50	14.44	0.07
$\exp(10 * (V_c - V_{cbdc}))$	3.46	0.02	0.00	0.00	0.00	0.00
$s_{cbdc} = \frac{1}{1+\exp(10*(V_d - V_{cbdc}))+\exp(10*(V_c - V_{cbdc}))}$	0.00	0.00	0.00	0.00	0.06	0.93

Note: The table decomposes the aggregate CBDC share s_{cbdc} in the special case (G60), where all households are assumed to have the same private utilities, $V_{i,j} = V_j$ for $j \in \{c, d, cbdc\}$, into the private utility differences, the exponential transformations of these utility differences under different β and the resulting s_{cbdc} (G60). In the table, V_j is calculated from averaging $V_{i,j}$ across all households in the estimation sample used in specification (9) in Table G20 of the Online Appendix G.2.4. The private utilities from deposits and cash are fixed and unchanged by the presence of CBDC, with $V_d = 2.97$ and $V_c = 0.71$. Assuming CBDC attributes are identical to those under the baseline design, then V_{cbdc} only changes with the CBDC-specific effects that range from being cash-like to being deposit-like (captured by the values of $\boldsymbol{\gamma}_{cbdc}/\widehat{\boldsymbol{\gamma}}_d$ and $\eta_{cbdc}/\widehat{\eta}_d$ ranging from zero to one as shown in the column title).

comparing the cases when the CBDC-specific effects (captured by the values of $\boldsymbol{\gamma}_{cbdc}/\widehat{\boldsymbol{\gamma}}_d$ and $\eta_{cbdc}/\widehat{\eta}_d$) take values of 1 and 0.8, which result in a small negative $(V_d - V_{cbdc})$ and a small positive $(V_d - V_{cbdc})$, respectively, but lead to a very different s_{cbdc}. Intuitively, network effects play a more important role in determining s_{cbdc} when the two products give similar private utilities. If CBDC gives a much higher private utility than deposits, then it would attract a lot of demand and reach a dominant position anyways, in which case network effects are not very important in affecting the asset shares.

Figure G22 visualises this mechanism by plotting s_{cbdc} in the special case (G60) against the utility difference $(V_{cbdc} - V_d)$ or the underlying changes in the CBDC-specific effects. As shown in Figure G22a, when V_{cbdc} increases relative to V_d, s_{cbdc} increases gradually in the absence of network effects. In contrast, with strong network effects, s_{cbdc} starts to increase a lot when V_{cbdc} becomes similar to V_d. The shaded area shows the values of $(V_{cbdc} - V_d)$ that correspond to the CBDC-specific effects ranging from being cash-like to deposit-like. To show the mapping from $(V_{cbdc} - V_d)$ to the underlying CBDC-specific effects, Figure G22b plots s_{cbdc} in the shaded area of Figure G22a but against a different x-axis.

Figure G23 plots s_{cbdc} in the general case when households have different private utilities and there is no closed-form expression for s_{cbdc}. Figures G22 and G23 show almost identical patterns, implying that the mechanisms illustrated using the special case above would still hold in general.

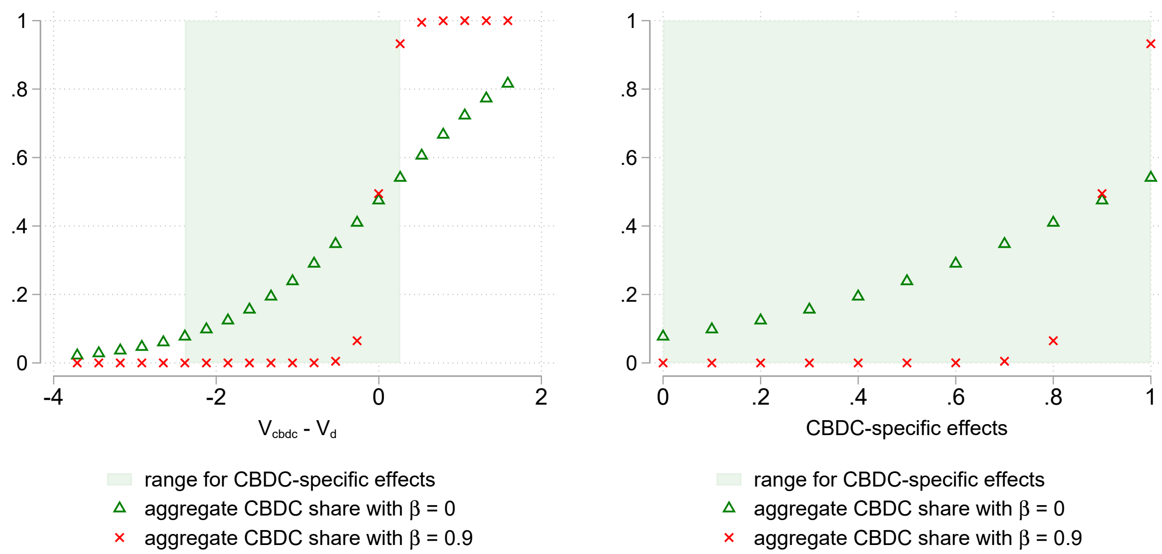
G.3.3 Counterfactual Results With and Without Network Effects

Figure G24 shows the predicted aggregate CBDC shares s_{cbdc} under a baseline design of CBDC against different assumptions on $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc} using different values of β. The black dotted line plots the s_{cbdc} calculated from the estimated parameters from the specification and sample used in the last column of Table G20, where $\widehat{\beta} = 0.273$. To compare the results with the baseline model without network effects and also cases where network effects are stronger, I use the same set of parameters (excluding $\widehat{\beta}$) and estimation sample to get the predicted s_{cbdc} under different values of β in the counterfactual analysis. In Figure G24, I also plot s_{cbdc} after setting β to 0, 0.5, 0.7, or 0.9. When $\beta = 0$, this extended model is reduced to the baseline model without network effects.

As can be seen from Figure G24, using the estimated $\widehat{\beta} = 0.27$, the range of predicted s_{cbdc} is slightly widened to 3–58%, compared to the case without network effects shown by the green line. The lower bound estimate in the absence of network effects is reduced to 3% because when $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc} are set to zero (the normalized value for cash), $V_{i,cbdc}$ is smaller than $V_{i,d}$ due to lower CBDC-specific effects and it is also smaller than $V_{i,c}$ due to CBDC attributes under the baseline design being worse than the cash attributes. As a result, the

Figure G22: Aggregate CBDC Share in the Special Case and the Role of Network Effects

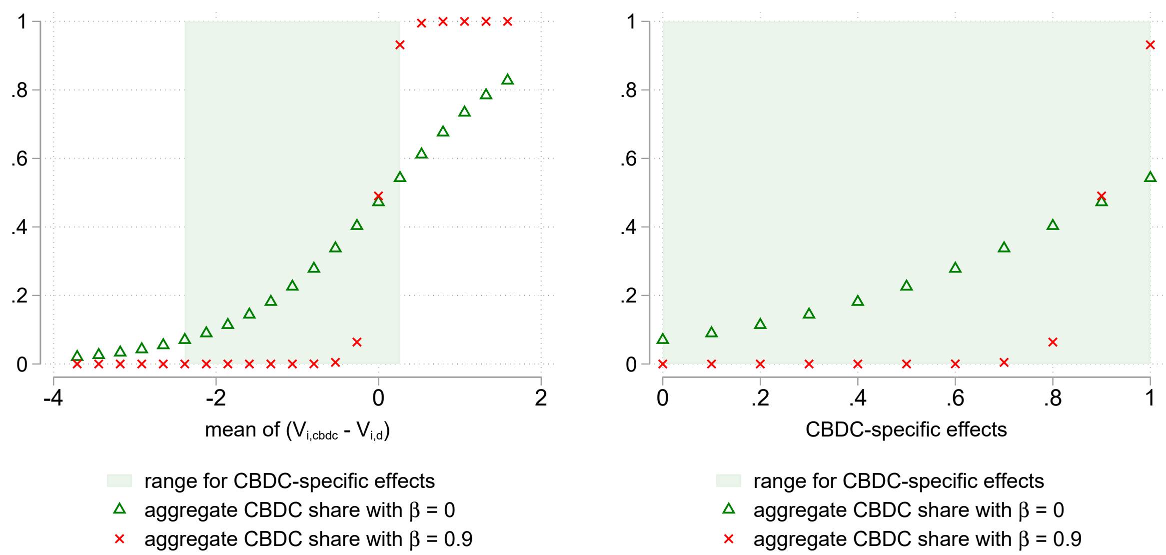
(a) s_{cbdc} against $(V_{cbdc} - V_d)$ (b) s_{cbdc} against CBDC-specific effects



Note: The figure plots the aggregate CBDC share s_{cbdc} in the special case (G60) where all households are assumed to have the same private utilities, $V_{i,j} = V_j$ for $j \in \{c, d, cbdc\}$. The private utility V_j is calculated by averaging $V_{i,j}$ across all households in the estimation sample used in specification (9) in Table G20 of the Online Appendix G.2.4. The private utilities from deposits and cash are fixed and unchanged by the presence of CBDC, with $V_d = 2.97$ and $V_c = 0.71$. Assuming CBDC attributes are identical to those under the baseline design, then V_{cbdc} only changes with the CBDC-specific effects (captured by the values of $\gamma_{cbdc}/\widehat{\gamma}_d$ and $\eta_{cbdc}/\widehat{\eta}_d$). Figure (a) plots s_{cbdc} against $(V_{cbdc} - V_d)$, where each value of $(V_{cbdc} - V_d)$ is obtained from changing the values of $\gamma_{cbdc}/\widehat{\gamma}_d$ and $\eta_{cbdc}/\widehat{\eta}_d$ from -0.5 to 1.5, with an increment of 0.1 each time. The shaded area is when the values of $\gamma_{cbdc}/\widehat{\gamma}_d$ and $\eta_{cbdc}/\widehat{\eta}_d$ range from 0 to 1. Figure (b) plots s_{cbdc} against different CBDC-specific effects ranging from being cash-like to being deposit-like, which corresponds to the shaded area of figure (a).

Figure G23: Aggregate CBDC Share in the General Case and the Role of Network Effects

(a) s_{cbdc} against mean of $(V_{i,cbdc} - V_{i,d})$ (b) s_{cbdc} against CBDC-specific effects



Note: The figure plots the aggregate CBDC share s_{cbdc} in the general case when households have different private utilities, $V_{i,j}$ for $j \in \{c, d, cbdc\}$. The mean of $(V_{i,cbdc} - V_{i,d})$ is calculated by averaging across all households in the estimation sample used in specification (9) in Table G20 of the Online Appendix G.2.4. The private utilities from deposits and cash, $V_{i,d}$ and $V_{i,c}$, are fixed and unchanged by the presence of CBDC, with the mean across households being $\overline{V_{i,d}} = 2.97$ and $\overline{V_{i,c}} = 0.71$. Assuming CBDC attributes are identical to those under the baseline design, then $V_{i,cbdc}$ only changes with the CBDC-specific effects (captured by the values of $\gamma_{cbdc}/\widehat{\gamma}_d$ and $\eta_{cbdc}/\widehat{\eta}_d$). Figure (a) plots s_{cbdc} against $(\overline{V_{i,cbdc}} - \overline{V_{i,d}})$, where each value of $(\overline{V_{i,cbdc}} - \overline{V_{i,d}})$ is obtained from changing the values of $\gamma_{cbdc}/\widehat{\gamma}_d$ and $\eta_{cbdc}/\widehat{\eta}_d$ from -0.5 to 1.5, with an increment of 0.1 each time. The shaded area is when the values of $\gamma_{cbdc}/\widehat{\gamma}_d$ and $\eta_{cbdc}/\widehat{\eta}_d$ range from 0 to 1. Figure (b) plots s_{cbdc} against different CBDC-specific effects ranging from being cash-like to being deposit-like, which corresponds to the shaded area of figure (a).

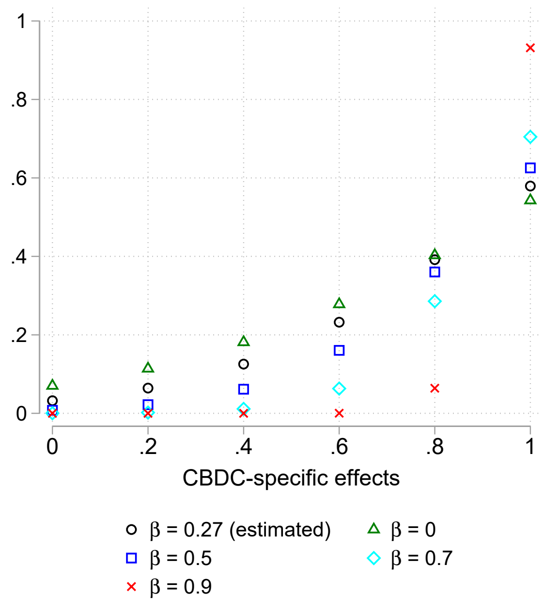
positive utility differences, $(V_{i,d} - V_{i,cbdc})$ and $(V_{i,c} - V_{i,cbdc})$, are amplified by $\frac{1}{1-\widehat{\beta}}$, which tends to result in a smaller $s_{i,cbdc}$ according to (G57).

Similarly, the upper bound estimate in the absence of network effects is increased to 58% because when $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc} take the estimated values for deposits, $V_{i,cbdc}$ is larger than $V_{i,d}$ due to CBDC attributes under the baseline design being better than the deposit attributes and it is also larger than $V_{i,c}$ due to higher CBDC-specific effects. The negative utility differences, $(V_{i,d} - V_{i,cbdc})$ and $(V_{i,c} - V_{i,cbdc})$, are amplified by $\frac{1}{1-\widehat{\beta}}$, which tends to make $s_{i,cbdc}$ larger according to (G57).

If network effects were very strong and CBDC were attractive, CBDC could reach a dominant position and push the demand for deposits and cash towards zero. As shown in Figure G24, with a baseline design for CBDC and deposit-like CBDC-specific effects, strong network effects under $\beta = 0.9$ could push the aggregate CBDC share towards one. However, with the estimated $\widehat{\beta}$, I find the network effects to be moderate. The baseline results are also robust to a wide range of β.

Table G22 compares the impacts of CBDC attribute changes on the percentage changes in aggregate CBDC share s_{cbdc} with and without network effects. The last two columns of Table G22 show the percentage changes in s_{cbdc} using different specifications and samples. The third column uses the specification and sample from the column (9) of Table G20, where $\widehat{\beta} = 0.27$. The last column uses the specification and sample from the baseline analysis without network effects, so the results in the last column are identical to the baseline results. As can be seen, when a given CBDC attribute changes relative to the baseline design, the resulting percentage change in s_{cbdc} is slightly larger in the presence of network effects.

Figure G24: Aggregate CBDC Shares With Different Strength of Network Effects



Note: The figure shows the aggregate CBDC shares s_{cbdc} under a baseline design for CBDC against different assumptions for the CBDC-specific effects (captured by the values of $\boldsymbol{\gamma}_{cbdc}/\widehat{\boldsymbol{\gamma}}_d$ and $\eta_{cbdc}/\widehat{\eta}_d$). At point of zero (one) on the x-axis, CBDC-specific effects are assumed to be cash-like (deposit-like), i.e., $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc} take the normalised values for cash (estimated values for deposits), so that $\boldsymbol{\gamma}_{cbdc}/\widehat{\boldsymbol{\gamma}}_d$ and $\eta_{cbdc}/\widehat{\eta}_d$ are both equal to zero (one). Each line plots s_{cbdc} that is predicted under a different value of the parameter β that captures the network effects. The dotted line plots s_{cbdc} using the estimated parameters from specification shown in the last column of Table G20, where $\widehat{\beta}$ is 0.27 and the estimation sample is different from the one used in baseline analysis. Using this sample and the estimated parameters (excluding $\widehat{\beta}$), I study different strength of network effects in the counterfactual analysis by setting β to 0, 0.5, 0.7, and 0.9, while keeping everything else the same. When $\beta = 0$, the extended model is reduced to the baseline model without network effects. Note that the predicted s_{cbdc} shown by the green line is slightly different from the baseline results due to the different sample and parameters used.

Table G22: Comparing the Impacts of Attribute Changes With and Without Network Effects

Design attribute	Change in attribute relative to baseline design	% change in s_{cbdc} with network effects	% change in s_{cbdc} without network effects
Interest rate	$0\% \rightarrow 0.1\%$	10 to 27	10 to 23
Budgeting usefulness	$0.7 \rightarrow 0$	-12 to -24	-7 to -14
Anonymity	$0.7 \rightarrow 0$	-7 to -16	-5 to -10
Bundling of bank service	$0 \rightarrow 1$	4 to 9	4 to 8

Note: The table shows the impact of the change in a given CBDC attribute on the percentage change in aggregate CBDC share s_{cbdc}. The second column describes the CBDC attribute change relative to the baseline design. For example, in the first cell of the second column, it means that CBDC rate increases from 0% under the baseline design to 0.1%. The third column shows the percentage change in s_{cbdc} when a given attribute changes relative to the baseline design in the presence of network effects, using the estimated parameters and sample from specification (9) of Table G20. The last column shows the percentage change in s_{cbdc} using the estimated parameters and sample from the baseline analysis without network effects. The lower (upper) bound estimate in each cell of the last two columns refers to the prediction based on the assumption that CBDC-specific effects are deposit-like (cash-like).

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